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PREDICT GENDER USING CONVOLUTIONAL NEURAL NETWORK

Memory in order to obtain a:
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Presented by:

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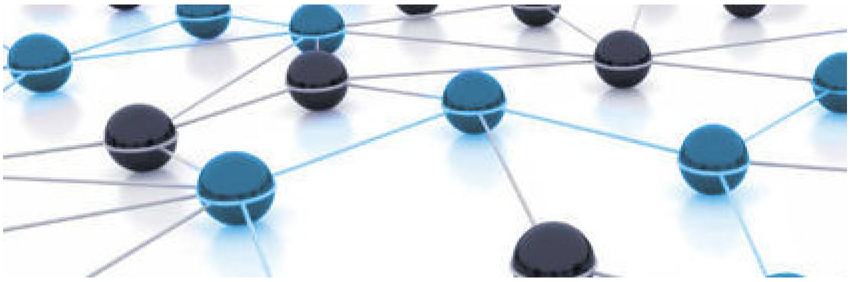

predict gender using convolutional neural network

Ghilani Mohammed Lazhari

Thesis to obtain the Phd Degree in

Electronics of embedded systems

Supervisors: Dr. Azeddine BENLAMOUDI

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Dedication

I dedicate this modest work to:

My beloved parents:
Ibrahim and **Zohra BAFOULOULOU** for their prayers and love. who have encouraged and supported me all the way until this work was finished.
I am sure that words will never be enough to thank you. may Allah bless you.

My dear brothers and sisters:
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All my teachers of the Department of Electronics and Telecommunications of Ouargla .

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To those who set me on the path of life, made me calm, and took care of me until I became a man, **(My mother)**.

And to my brothers and sisters, each in his name.

And to the souls of my ancestors, may God have mercy on them.

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To each and every one of you – Thank you.

Abstract

With the development of science and the increase of the need of safety, many techniques and methods have emerged, and Biometrics or so-called (biological properties, including fingerprint, face print, eye print, voice, hand geometry, and DNA) have given new dimensions to the process of identifying and verifying personal identity. It enabled specialists and researchers to use modern methods and advanced technologies in order to provide a high degree of accuracy and safety in the topic of identity verification.

In this memory, the method of determining gender is studied by the face using the convolution neural network, as this technique can adapt to collecting cases to perform the process of determining gender with the best results, and it is an effective technique that has been tried in many tests such as age and race determination.

At the end, this technique was demonstrated, and I did it through the results obtained.

Keywords

Biometrics, Face recognition, Gender recognition, Convolution Neural Network

Résumé

Avec le développement de la science et l'augmentation du besoin de sécurité, de nombreuses techniques et méthodes ont émergé, et la biométrie ou ce qu'on appelle (propriétés biologiques, y compris les empreintes digitales, les empreintes faciales, les empreintes oculaires, la voix, la géométrie de la main et l'ADN) ont donné de nouvelles dimensions à la le processus d'identification et de vérification de l'identité personnelle. Il a permis aux spécialistes d'utiliser des méthodes modernes et des technologies modernes avancées afin de fournir un haut degré de précision et de sécurité dans la question de la vérification d'identité. Dans cette memoire, la méthode de détermination il étudie la sexualité à travers le visage à l'aide du réseau neurone à convolution, comme cette technique peut s'adapter à la collecte de cas pour effectuer le processus de détermination du sexe avec les meilleurs résultats, et c'est une technique efficace qui a été essayée dans de nombreux tests tels que la détermination de l'âge et de la race. Et à la fin, cette technique a été démontrée, et je l'ai fait à travers les résultats obtenus.

Mote Clé

Biométrie, Reconnaissance de Visage, Déterminez le sexe, Réseau de Neurones à Convolution.

الملخص:

مع تطور العلم وازدياد الحاجة للأمان ظهرتالعديد من التقنيات والوسائل، وقد أعطت السمات الحيوية أو ما تسمي (الخواص البيولوجية والتي منها بصمة الأصابع - بصمة الوجه بصمة العين الصوت هندسة اليء الحمض النووي) أبعاداً جديدة لعملية التعرف والتوثق من الهوية الشخصية، فقد مكنت المختصين من استخدام الوسائل الحديثة والتقنيات الحديثة المتطورة وذلك من أجل تقديم درجة عالية من الدقة والأمان في مسألة التحقق من الشخصية

و في هده المذكرة ندرس كيفية تحديد الجنس بواسطة الوجه باستخدام الشبكة العصبية التفافية حيث ان هده التقنية يمكنها التكيف مع جمع الحالات لأداء عملية تحديد الجنس بأحسن النتائج و هي تقنية فعالة حيت تم تجريبها في العديد من اختبارات مثل تحديد العمر و العرق

وفي الاخير اظهرت هذه التقنية فعليتها من خلال النتائج المحصل عليها

الكلمات الدلالية:

السمات الحيوية ،تحديد الجنس ، التعرف على الوجه ،الشبكة العصبية التفافية

Contents

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Acronyms

AAM	Active Appearance Model
BSIF	Binarized Statistical Image Features
CNN	Convolutional Neural Network
CPU	Central Processing Unit
DML	Deep Metric Learning
GPU	Graphics Processing Unit
HCI	Human Computer Interaction
IDE	Integrated Development Environment
LBP	Local Binary Patterns
LFW	Labeled Faces in the Wild
LPQ	Local Phase Quantization
ROI	Region Of Interest
SVM	Support Vector Machine
SIANN	Shift Invariant Artificial Neural Networks

General Introduction

Biometrics helps automatic identification of people based on physical or behavioral characteristics such as the face, fingerprint, iris, hand, voice, gait, and signature. The face is one of the most important biometric traits. By analyzing the face we get a lot of information such as age, gender, ethnicity, identity, expression, etc.

Gender contains a wide range of information regarding the characteristics of the difference between male and female [1]. Gender classification could be of important value in human-computer interaction, such as personal identification. Also, it is a useful preprocessing step for face recognition. A computer system with the capability of gender classification has a wide range of applications in basic and applied research areas, including man-machine communication, security, law enforcement, demographics studies, psychiatry, education, and telecommunication, etc. The field of face recognition has been explored by many researchers. But in gender recognition or classification, only a few works have been reported. The face image is used for classifying the gender, so the gender classification process can make face recognition twice as fast by reducing the search time for recognizing the person.

The rest of this memory is as follows: **Chapter** 1 gives an overview of soft biometric systems and compares it with the traditional techniques, it also gives a general idea about the different types of soft biometrics, including the mechanism of soft biometric system work. **Chapter** 2 illustrates the meaning of gender recognition, its importance in human-computer interaction, and describes the steps of gender classification. **Chapter** 3 includes the definition of the main method used for gender classification completion which is Convolutional Neural Network (CNN), it also describes the architecture and the building blocks particularly. And explains the areas of use and application as well. **Chapter** 4 explains the experimental phase.

The environment of the gender classification system, and the different development tools that have been used. Then we present the results and conclusion.

1

Soft Biometric

1.1 Introduction

Soft biometric techniques identify people using distinct physical or behavioral features. These features are very discriminative although can rarely be described using labels that can be understood by people. Identification of situations where the subject's biometric signature can be obtained and only permits identification of those subjects whose biometric signature has previously been recorded. Soft biometrics concerns label that people use to describe each other. Although each trait/ label can have reduced discriminative capability, they can be combined for identification [2] and fusion with traditional'hard' biometrics [3].

One of the main advantages of soft biometrics is their relationship with human description; humans naturally use soft biometric traits to identify and describe each other. Beyond identification, soft biometrics also allow retrieval. This is achieved by bridging the semantic gap between biometric measurements and human descriptions. The human face is crucial for the identity of persons because it contains much information about personal characteristics. It provides lots of useful information, including the person's identity, gender, ethnicity, age, emotional expression, etc. Thus, the face image is important for most biometrics systems.

1.2 Definition

A biometric-based security system is almost impossible to be fooled. The word biometric is a composite word, bios, which refers to life, and metron, which refers to measure, coming from the Greek language. [4]. Soft Biometric is sometimes defined as an anatomical or behavioral characteristic that provides some information about the identity of a person but does not provide sufficient evidence to precisely determine the identity that can be referred to as a soft biometric trait. Personal attributes like gender, ethnicity, age, height, weight, eye color, scars, marks, tattoos, and voice accent are examples of soft biometric traits. Soft biometric information complements the identity information provided by traditional (primary) biometric identifiers such as fingerprint, face, iris, and voice. Hence, utilizing soft biometric traits can improve the recognition accuracy of primary biometric systems [5].

1.3 Previous works on soft biometric

Defining work on soft biometrics. It should be an overview in order not to appear to be a comprehensive case, but it is an excellent choice for scientific studies carried out.

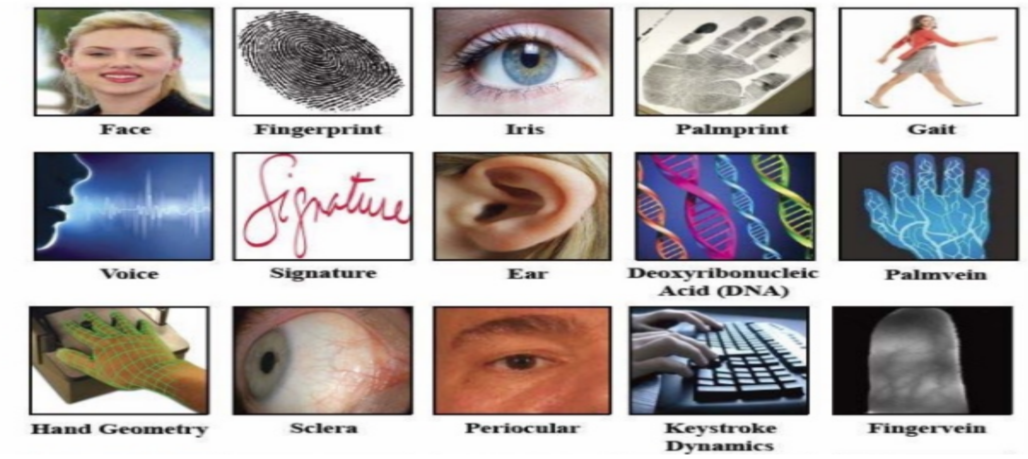

Figure 1.1: Examples of properties we use to get to know people

1.3.1 Facial Soft Biometrics

Previous work carried out on soft biometrics is mostly aimed at pretreatment. in his face Identifying a person, for example, uncovering and removing a beard Improves recognition results, regardless of information regarding the presence of a file beard [6–8].

Color-dependent soft facial features (eye, skin, and hair color) are most commonly used Facial identifiers, which are primarily mentioned by humans when photographing anonymous individuals. Skin challenges Classification on the one hand the low spread of different skin colors in color space, and as a consequence, on the other hand, the high illumination dependence of classification. Latter is described in various skin locus papers [9]. Hair color is detected by similar techniques like skin color and often researched along but has more broadly scattered color categories [10]. A method for human head detection based on hair–color is proposed through the use of Gaussian mixture density models describing the distribution of hair color [11]. The fuzzy theory is used to detect faces in color images, where two fuzzy models describe the skin color and hair color, respectively.

The discovery of eye color, unlike other soft biometrics of the face, is the subject of new research [12], likely due to the fact that 90% of humans have brown eyes. The advantage of eye color detection is the availability of all necessary information present in the iris for pattern analysis, in other words, iris color is a free side effect.Work on visualizing the iris. Texture and color can be found [13],The authors combine the color of the iris with the ngerprint to improve performance for unimodal systems [14]. Iris color used to support a successful iris indexing method.

The beard and mustache are not visible Rather, they are a hindrance to face recognition, which is why they are removed as a step before processing [15] an algorithm for removing the beard from the image of the person with the beard is displayed using the concept of structural similarity and coordinate transformations

Figure 1.2: Facial Soft Biometrics

1.3.2 Body Soft Biometrics

The main features of the body are height, gait, body weight, and color of clothes, so it can be extracted remotely. The best distinction is provided through gait detection, Why gait is sometimes referred to as a classic biometric gait since gait is a complex pattern that includes not only some human parameters but also behavioral information. It is one of the few features that can be collected remotely [16].The author uses lights placed on the joints of the human body to record people's gait patterns. The author explains how observers can recognize familiar people walking only through traces of light [17]. The spatio-temporal prediction is extracted by the moving silhouette, the main components are subsequently analyzed to discard the useless information, and finally the supervised pattern classification techniques are implemented in the eigenspace with close dimensions. To define this analysis, the structural and behavioral characteristics of the gait are captured [18] . The system integrates prediction results from gait and semantic information in order to identify biometric system users. A modern approach based on soft biometrics is provided [19].

To automatically estimate altitude, it is necessary to familiarize yourself with the basic gauge, which can be adopted through the various silhouette extraction techniques used to recognize gait. Height is a feature used for human tracking or as an aid to other algorithms, such as walking [20].In which single and multiple calibrated camera systems are used for elevation estimation, estimation is made by calculating the height associated with the real world coordinates estimated in the camera images.

The only paper with a weight scale that uses a weight scale are the users of the fingerprint recognition system. By exploiting the body weight and fat measurements, the authors reduced the overall system error rate by 2.4 %

Figure 1.3: Examples of Body Soft Biometrics

Weighing is a soft new biometric feature that remains to be explored especially in terms of its measurement.

1.3.3 Accessory soft biometrics

New soft biometrics allow accessories to be included among these traits. Accessories can actually relate to personal characteristics. Like discovering glasses as the pioneer of eyeglasses Jiang et al [21].Detect classic edges on an image with a pre-processed gray plane. And areas of the face and index glasses are observed I searched and found the most successful area to locate glasses is the part of the nose Between the eyes. A different approach to extracting glasses [22],where the facial model is established on the basis of Delaunay Trinity. A 3D method for detecting eyeglass frames [23], in which the three-dimensional features are obtained by means of a stereoscopic vision system. Best Spectacle detection results have so far been achieved on thermal images [24].

Figure 1.4: Examples of Accessory soft biometrics (Glasses)

1.3.4 Combined soft biometrics

The soft vital features individually are not distinct and permanent, they are a mixture Who can outrun its limits ?. In this context, many recent papers deal with fusion of classical biometry and soft biometry or exclusively with fusion of soft biometric traits. An example for latter is the work [25]. The authors propose algorithms for gender, body size, height, cadence, and stride using a novel gait analysis tool. [26] height, and appearance are extracted from videos and exploited in a multiple camera video surveillance scenario in order to track the subjects that cross the surveillance network. [27] a novel approach for recognizing the gender, ethnicity and age with facial images is proposed. The approach is a novel combination of Gabor filter, Adaboost learning and support vector machine classifier. The experiment results of the system based on this approach are reported to show a good performance. A further hybrid classification based on gender and ethnicity is considered [28]. The hybrid approach consists of an ensemble of radial basis function networks and inductive decision trees. The authors show robustness and good perfomance. A different approach for analysis in hybrid soft biometric systems is provided in [18], where semantic information (which corresponds to soft biometric classifiers) is manually extracted from a series of videos. Using the analysis of variance the authors select a pool of traits which are considered the most representative. Those traits are then used together with gait information. The authors demonstrate that the additional information provided by the semantic traits increases the performance of the people recognition system based on gait. [29] go one step further and study the relation of human body measures, which allows for certain applications the prediction of missing body measures [30]. The authors propose an approach for people search in surveillance data, characterized by three main elements: sensors, body parts, and their attributs. The body parts and attributes are here closely related to soft biometrics. [31] a theoretical analysis of reliability performance of soft biometrics employed for identification is presented. In this work identification errors due to collision are considered. The statistical behavior of soft biometric systems is analyzed in the asymptotic setting of a large number of facial and body feature categories

1.4 Types of soft biometrics

Personality traits such as gender, ethnicity, age, and height are examples of soft vital traits. Soft biometric complements the identification information provided by traditional biometric identifiers. The use of soft biometric features can improve the recognition accuracy of primary biometric systems.

1.4.1 Age

The automatic age rating aims to assign a sticker to a face in relation to the exact age (age estimate) (See Figure. 1.5) or the age group (age rating) to which it belongs. This is a difficult problem because the appearance of a particular face varies due to changes in posture, expressions, lighting, and other factors such as makeup, image degradation caused by blur, noise, etc. In addition to these common difficulties with standard face recognition problems, aging is a very complex process that is extremely difficult to design. People of the same age are completely different, for example, environment, lifestyle, genetics, etc. The global age rating model is annoying. Several representations of facial images have been studied for age estimation such as anthropometric models. Active Appearance Model (AAM), partial space of aging pattern, and age bifurcation. A comprehensive review of age representation methods can be found in [32]. With regard to age classification schemes, current approaches are based on either pure classification or regression analysis. Perhaps among the pioneering studies on age classification are those proposed by Kwon and Lobo and Lanitis *et al.* [33].

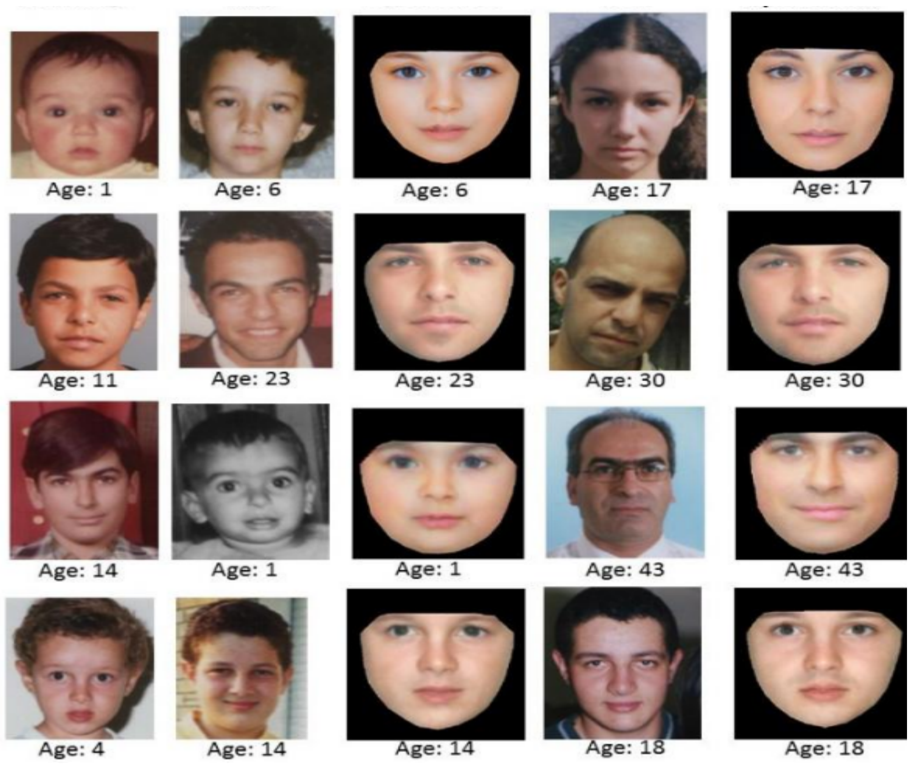

Figure 1.5: An example of the age advantage of soft biometrics

1.4.2 Gender

Recognizing gender from unfettered facial images is a challenging task due to the high degree of alignment, posture, expression, and contrast in lighting. In earlier works, gender recognition from unconstrained facial images is done through the use of image alignment, exploiting multiple samples for each individual to improve the learning capacity of the classifier, or learning gender based on previous knowledge about demographics and demographic distributions of a dataset. However, aligning the images increases the complexity and time of calculation, while using multiple samples or having prior knowledge about data distribution is unrealistic in practical applications (See Figure. 1.6).

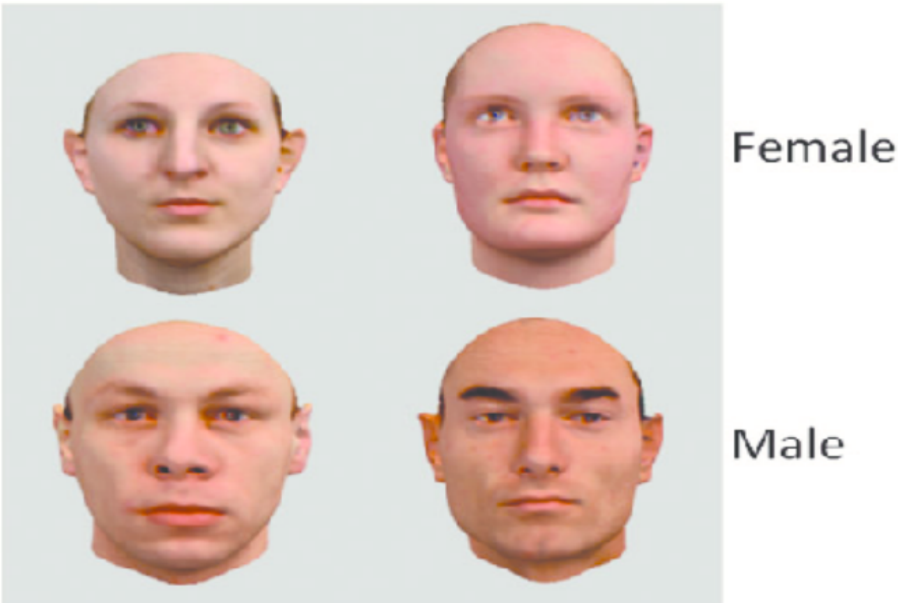

Figure 1.6: An example of the gender advantage of soft biometrics

1.4.3 Ethnicity

Ethnicity is a social group called people who are similar on the basis of common features that distinguish them from other groups such as a common set of traditions, origin, language, history, society, culture, nation, religion, or social treatment within their area of residence [34] (See Figure. 1.7).

Figure 1.7: An example of ethnicity for soft biometrics

1.4.4 Height

Figure 1.8: Example of height for soft biometrics

Estimating people's height from a single image is needed in many areas such as subject identification for surveillance purposes, pedestrian distance estimation for autonomous driving [35], and automated garment fitting in online stores. However, since people's apparent height is affected by camera distance and focal length, assessing someone's real height only from the image is difficult (See Figure. 1.8).

In this part, we talked about many soft biometric types and their importance in the identification of persons. And there are many other soft biometrics types. but the one related to our memory is gender recognition.

1.5 How Biometrics Works?

Biometric systems may seem complex and difficult to study, but they all use the same stages which have been described below (1.9):

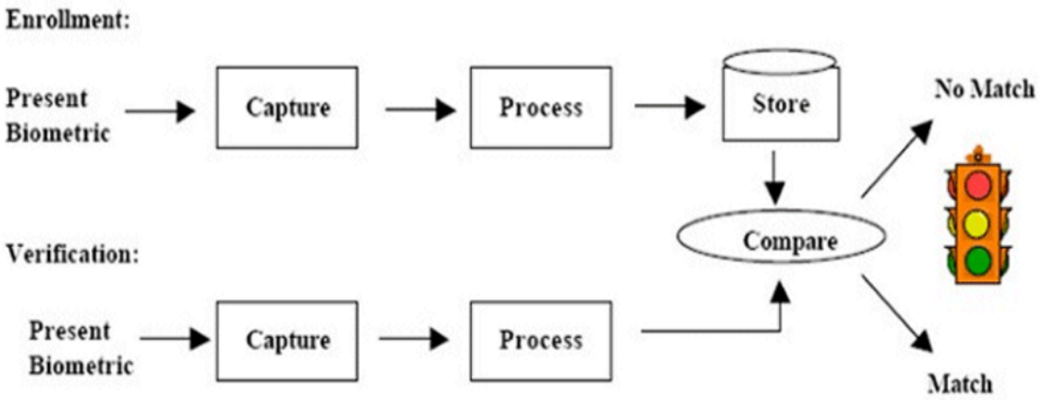

Figure 1.9: Example of how biometrics work

1.5.1 Enrollment And Storage

The first time you use the biometrics system, it records basic information about you, such as your name or identification number. Then it takes a photo or records your theme, for example, hair color, iris, eye or facial features. Unlike what you might see in movies, most systems do not store the image or the full recording. Instead, they analyze your features and translate them into a symbol or graph based on the format the wizard understands. Some systems also record this data on a smart card that you carry with you to re-enter it in the event of a malfunction in the data.

1.5.2 Authentication

Biometric authentication is simply the process of verifying your identity using your measurements or other unique characteristics of your body, then logging you into a service, an app, a device, and so on. Then the system uses your information to compare you against a database and enters your information in service.

1.5.3 Comparison

The next time when we use the system, it compares the trait you present to the information on file. Then, it either accepts or rejects that you are who you claim to be.

Systems also use the same three components:

- A sensor that detects the characteristic being used for identification
- A computer that reads and stores the information
- Software that analyzes the characteristic, translates it into a graph or code and performs the actual comparisons

1.6 Problematic of soft biometrics

Generally, surveillance camera networks provide us with images with an insufficient resolution for facial recognition. Therefore, the need for additional tools to deal with low-quality images is inevitable, and here the role of soft biometrics comes. As is known, most of the soft biometrics traits can be extracted from low-quality images. These traits provide information about the individual but lack uniqueness and permanence to differentiate sufficiently between two individuals, unlike traditional biometrics which provides information about the identity of the person.

The main aim of this memory is to improve the accuracy and the computational time of soft biometrics systems. This latter can be very assistant to biometrics systems in terms of accuracy and identification time. Most of the existing works focused only on the demographic traits which can be extracted from the face. For satisfactory results, it is better to improve the three main stages of traditional soft biometrics systems which are image preprocessing, feature extraction, and trait estimation.

1.7 Characteristics, Advantages and Limitations

Soft biometrics has carried in some extent the attributes of classical biometrics over, as the idea of identification management based on who you are is still pursuit. The traits provide weak biometrical information about the individual and correspondingly have inherited the predicates to be universal, measurable and acceptable; the trait's detection algorithm(s) performance should be able to meet the application's requirements. To a certain degree also the aspects uniqueness, permanence and circumvention play a role for soft biometrics, but are treated to a greater extend flexible. Recently, soft biometric traits have been employed to preliminary narrow down the search of a database, in order to decrease the computational time for the classical biometric trait. Another application approach is to fuse soft biometrics and classical biometric traits to increase the system reliability. Soft biometrics impart systems substantial advantages: they can be partly derived from main detected classical biometric identifier, their acquisition is non obtrusive and does not require enrolment; training can be performed in advance on individuals out of the specific identification group. Summarizing soft biometric traits typically are:

- Human compliant: Traits are conform with natural human description labels.
- Computational efficient: Sensor and computational requirements are marginal.
- Enrolment free: Training of the system is performed off–line and without prior knowledge of the inspected individuals.
- Deducible from classical biometrics: Traits can be partly derived from images captured for primary (classical) biometric identifier (e.g. eye color from iris images).
- Non intrusive: Data acquisition is user friendly or can be fully imperceptible.
- Identifiable from a distance: Data acquisition is achievable at long range.
- Not requiring the individual's cooperation: Consent and contribution from the subject are not needed.

- Preserving human privacy: The stored signatures are visually available to everyone and serve in this sense privacy.

The plethora of utilities related to soft biometrics comes along with limitations, namely the lack of distinctiveness and permanence. A system consisting of fused soft biometric traits can overcome the lack of distinctiveness associated with a single trait. The lack of permanence affects and designates feasible applications.

1.8 Performance Evaluation systems soft biometric

Accuracy is used as a statistical measure to find out whether a dual-state test has been correctly identified or excluded. That is, accuracy is the ratio of true (positive and negative) predictions to the total number of cases examined [36] To illustrate the context through semantics, it is often referred to as ”rand’s accuracy.” [37] is the test parameter.

$$Accuracy = \frac{RP + RN}{RP + RN + PE + NE} \tag{1.1}$$

where:

- RP = Real positive
- PE = Positive error
- RN = Real negative
- NE = Negative error

1.9 Application

Biometric techniques are applied in several areas and their scope potentially covers all areas of security where it is necessary to know the identity of individuals. The applications can be divided into three main groups:

- Commercial applications:
  Such as computer network opening, electronic data security, e-commerce, Internet access, credit card, physical access control, cell phone, management of medical records, remote study, etc
- Government applications:
  Such as national identity card, driver's license, social security, border control, passport control, etc.
- Legal applications:
  such as body identification, criminal search, terrorist identification, etc

1.10 Conclusion

In this chapter we studied the different soft biometrics and we presented the features, advantages, limitations, and its problematic.

Biometrics checks can be productively used in very wide areas of life by utilizing computing frameworks. And since our memory is about gender we will focus in the next chapters on face and how to recognize the gender of a person through it.

2

Gender classification

Contents

2.1 Introduction

Gender classification has become an essential task in Human Computer Interaction (HCI). Gender classification is used in an immense number of applications like passive surveillance, control in smart buildings (restricting access to certain areas based on gender) and the major stores and the security investigation. Even now we still use facial features to reveal gender is done by using methods like Gabor wavelets, artificial neural networks (the one we used in this work), and Support Vector Machine (SVM). Research has shown that the disparity between facial masculinity and femininity can be utilized to improve performances of face recognition applications in biometrics, human-computer interactions, surveillance, and computer vision [38]. In particular, recognizing human gender is important because people respond differently depending on gender. In sum, a successful gender classification approach can boost the performance of many other applications, including person recognition and smart human-computer interfaces.

2.2 Definition

Gender classification is to tell which gender (male/female) of a person according to his/her face. It is an easy job for humans, but it is a challenge for computers. Gender classification can be an important goal in human-computer interaction, such as personal identification [1]. Also, it is a useful preprocessing step for face recognition. So, a gender classification system uses the face of a person from a given image to tell the gender of the given person.

2.3 Gender in computer vision

While a human can easily differentiate between genders, it is a challenging task for computer vision. In this section, we study the methods of human gender recognition in images and videos. We focus our attention on easily observable characteristics of a human which would not require the subject's cooperation or physical contact. Most researchers have relied on facial analysis, while some workers have been reported using the whole body, either from a still image or using gait sequences. We concentrate on approaches using 2-D (rather than the more costly 3-D) data in the form of still images or videos [39].

In general, a pattern recognition problem such as gender recognition, when tackled with a supervised learning technique, can be broken down into several steps which are object detection, preprocessing, feature extraction, and classification. In detection, the human subject or face region is detected and cropped from the image. This is followed by some preprocessing, for example, geometric alignment, histogram equalization, or resizing. In feature extraction, representative descriptors of the image are found, after which selection of the most discriminative features may be made or dimension reduction is applied. As this step is perhaps the most important to achieve high recognition accuracy, we will provide a more detailed review in later sections.

Lastly, the classifier is trained and validated using a data-set. As the subject is to be classified as either male or female, a binary classifier is used, for example, SVM, Ada-boost, CNN, and Bayesian classifier.

2.4 Gender recognition methods

To properly study the characteristics of the different methods, a large data set is usually needed to properly test and measure the performance of the approach. Gender image datasets can be grouped into two broad categories: restricted and unrestricted. Examples of restricted data sets are better detailed below [7, 40, 41].

2.4.1 Face preprocessing

The preprocessing phase of the face consists of three steps, which is the detection of the face using the Viola and Jones algorithm [42], the imaging architecture is designed to locate the eye, correct the intensity of the face, and then cut the face [43–46] (See Figure 2.1).

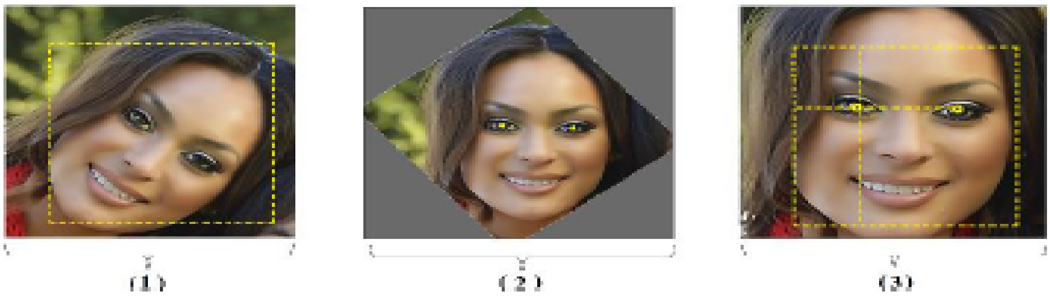

Figure 2.1: Example of face alignment: (1) face detection, (2) eye localization, and (3) face cropping

2.4.1.A Facial parts detection

To discover the location of the face in the image. We use Viola Jones detection algorithm And the trainer detection classification form. By default, the detector is created to detect faces, But it can be used to discover things, too

2.4.1.B Pose correction

To correct the situation we must apply the 2D shift on the center of the eyes to correct pointing to. As in [47], we rotate the face clockwise θ around the center of the image (C_x, C_y). The angle is calculated using the formula in the equation below:

$$\theta = tan^{-1}(\frac{R1_y - L1_y}{R1_x - L1_x}) \tag{2.1}$$

Then we find the new coordinates of the eye center using the following equations 2.2:

$$\begin{aligned} L'_x &= C_x + (L_x - C_x).cos(\theta) - (L_y - C_y).sin(\theta) \\ L'_y &= C_y + (L_x - C_x).sin(\theta) + (L_y - C_y).cos(\theta) \\ R'_x &= C_x + (R_x - C_x).cos(\theta) - (R_y - C_y).sin(\theta) \\ R'_y &= C_y + (R_x - C_x).sin(\theta) + (R_y - C_y).cos(\theta) \end{aligned} \tag{2.2}$$

Through the image below, we know how to correct position (See Figure. 2.2)

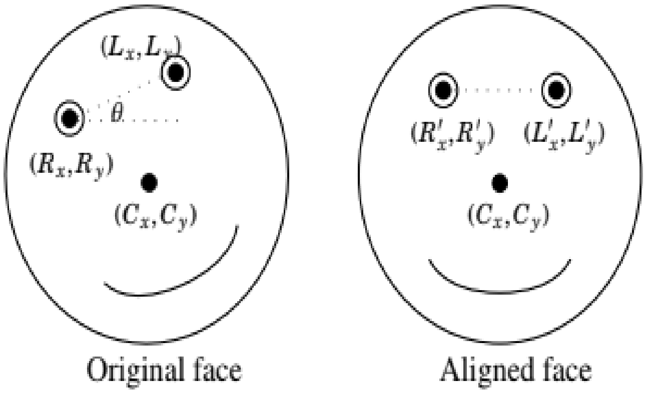

Figure 2.2: Facial pose correction step.

2.4.1.C Face region selection

To select the region of interest, we calculate the distance d between the new coordinates of the center points of the eyes where $d = |R'_x - L'_x|$. Then we crop the image based on factor values k_side,k_top, and k_bottom [46]. In our work and by experiments, we set the value of these factors as follow: $k_side = 0.5$, $k_top = 1$, and $k_bottom = 1.75$. Face clarifies Region Of Interest (ROI) which will be used in the feature extraction phase (See Figure. 2.3).

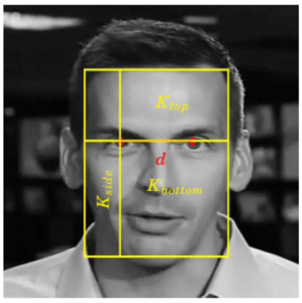

Figure 2.3: Face region selection step.

2.4.2 Features extraction

In this module implement discriminative Deep Metric Learning (DML) which is an algorithm employed the computer technology that determines the locations and sizes of human faces in arbitrary (digital) images. It detects facial features and ignores anything else, such as buildings, trees, and bodies [48]. Face detection can be regarded as a more general case of face localization. In face localization, the task is to find the locations and sizes of a known number of faces.

We examined four famous tissue descriptors that can be applied to extract features from the face image like Local Binary Patterns (LBP), Local Phase Quantization (LPQ), Binarized Statistical Image Features (BSIF), and CNN. We explain below those CNN that we uses in our work.

2.4.2.A Convolution Neural Network

The convolutional neural network is one of the main categories for performing image recognition and image classifications. Uncover objects, recognize faces, etc.

CNN image ratings take an entry image, process, and classify it into certain categories for example (Dog, Cat, Tiger, Lion ...etc). CNN models for deep learning of training and testing, each input image you will pass through a series of layers of wrapping layers with filters (Kernals), grouping, fully connected layers, and application of the Softmax function to classify an object with probability values between 0 and 1 [49]. The next figure (4.1) is the full flow of CNN to process the input image and classify objects based on the values.

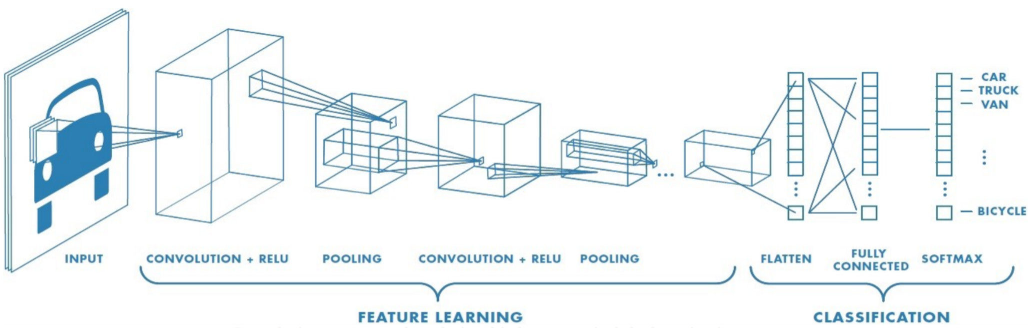

Figure 2.4: Example of a convolutional layered neural network

2.4.3 Classification

To identify the gender from facial photos. Several systems are able to automatically determine the gender from facial images quickly. This major interest arises from a variety of applications, especially in the retail and video surveillance industries. As for the classification, there are many algorithms working in this field and it has a high tribal rate, for example, the SVM technique that appeared in 2005 by Jane where the experiment was performed on 500 images of 250 female, 250 male, and 96 % accuracy. In our work, we use CNN as a classifier either.

2.5 Benchmark databases

In this section we revisit the databases used for the experiments, we propose a test protocol and explain the metrics used to evaluate the results.

Figure 2.5: Examples faces from Gallagher's (upper row) and LFW (bottom row) databases

We used Gallagher [50] and Labeled Faces in the Wild (LFW) [51] (See Figure. 2.5 databases for this experiment, both containing images captured in unrestricted conditions. Gallagher database consists of 28231 classified faces collected from Flickr photos that are publicly available (See Figure 2.5. It was previously used to classify gender in unrestricted conditions [50], but there is no common and specific trial protocol, and the results obtained by somewhat different authors cannot be compared using this database. LFW contains 13233 named images from 5749 individuals collected from the web. There is previous work on gender recognition using this database [51], and a measurement protocol to standardize gender recognition experiences in this field The database was suggested in [51].

2.6 Metrics

To compare the performance of different tested schemes, we use Accurate Metrics (ACC).

$$ACC = (\frac{TP + TN}{P + N}) \tag{2.3}$$

Where:

- TP the number of test samples correctly classified as positive
- TN the number of test samples correctly classified as negative
- P the total number of positive test samples
- N the total number of negative test samples

2.7 Conclusion

Automatic classification by gender has become relevant to a growing number of apps, especially since the advent of social platforms and social media. However, the performance of current methods on photorealistic images remains significantly underrepresented, especially when compared to the massive jumps in performance recently reported for the related face recognition task. In this chapter, we demonstrate that by learning representations through the use of convolutional deep neural networks (CNN), a significant increase in performance in these tasks can be obtained. To this end, we use a simple convolutional network architecture to please us even when the amount of data is limited.

3

Convolution Neural Network

Contents

3.1 Introduction

In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery . They are also known as Shift Invariant Artificial Neural Networks (SIANN), based on their shared-weights architecture and translation invariance characteristics. They have applications in image and video recognition, recommender systems, image classification, medical image analysis, natural language processing, and financial time series. CNNs are regularized versions of multilayer perceptrons. Multilayer perceptrons usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The ”fully- connectedness” of these networks makes them prone to overfitting data. Typical ways of regularization include adding some form of magnitude measurement of weights to the loss function. CNNs take a different approach towards regularization: they take advantage of the hierarchical pattern in data and assemble more complex patterns using smaller and simpler patterns. Therefore, on the scale of connectedness and complexity, CNNs are on the lower extreme. Convolutional networks were inspired by biological processes in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field. CNNs use relatively little pre-processing compared to other image classification algorithms. This means that the network learns the filters that in traditional algorithms were hand-engineered. This independence from prio knowledge and human effort in feature design is a major advantage.

3.2 Definition

CNN is a type of deep learning model for processing data that has a grid pattern, such as images, which is inspired by the organization of animal visual cortex and designed to automatically and adaptively learn of features, from low- to high-level patterns [52]. CNN is a mathematical construct that is typically composed of three types of layers (or building blocks): convolution, pooling, and fully connected layers. The first two, convolution and pooling layers, perform feature extraction, whereas the third, a fully connected layer, maps the extracted features into the final output, such as classification.

3.3 History

In 1980. Kunihiko Fukushima introduced two basic types of layers in CNNs [53]. The first is convolutional layers that contain modules whose receptive fields cover a patch of layer and this unit is called a filter. The second is the downsampling layers. Contains units whose receptive fields cover spots of previous convolutional layers. This unit usually calculates the average unit activation in its patch. This shortcut helps to correctly categorize objects in visual scenes even when objects are offset.

Yann LeCun et al. (1989) [54] use reverse propagation to learn the coefficients of a torsion nucleus directly from the handwritten number images. Thus the learning was completely automatic, performed better than manual laboratory design, and was suitable for a wide range of image recognition problems and types. This approach has become the basis of modern computer vision.

Similarly, W. Zhang et al algorithm proposed architecture and training in 1991 [55] and was applied to medical image processing [56] and automatic detection of breast cancer in mammography. Although CNNs were invented in the 1980s, in 2000 they experienced rapid overlaps on Graphics Processing Unit (GPU)s. The first GPU implementation of CNN was described in 2006 by K. Chellapilla et al. Its implementation was 4 times faster than the equivalent Central Processing Unit (CPU) execution. Subsequent use also used GPUs, initially for other types of neural networks (different from CNNs), especially unmonitored neural networks.

Subsequently, a similar GPU-based CNN by Alex Krizhevsky et al. won the ImageNet Large Scale Visual Recognition Challenge 2012 [57]. A very deep CNN with over 100 layers by Microsoft won the ImageNet 2015 contest.

3.4 Applications

The simple applications of CNNs that we can see in daily life are obvious choices, such as facial recognition software, image classification, speech recognition software, etc. These are terms that we know, as normal people, that make up a large part of our daily life. Some of the main applications of CNN we will mention:

- Convolutional neural networks can be used to analyze documents. Not only is this useful for handwriting analysis, but it also has a great interest in recognizers. In order for the machine to scan an individual's writing, then compare it to its broad database
- s are also used for more complex purposes such as natural history groups. These groups act as major players in documenting key parts of history such as biodiversity, evolution, habitat loss, biological invasion and climate change.
- CNNs can be used to play a key role in combating climate change, particularly in understanding why we see such drastic changes and how we can experience mitigation.
- CNNs have already brought in a world of difference to advertising with the introduction of programmatic buying and data-driven personalized advertising.
- Gray Zone is being introduced into CNNs to provide a more realistic picture of the real world. Currently, CNNs operate pretty much the same as a machine, seeing right and wrong value for each question. However, as humans, we understand that the real world plays with a thousand shades of gray. Allowing the machine to understand and manipulate fuzzy logic will help it understand the gray area that we humans live in and strive to work against.

3.5 Architecture

The CNN architecture includes several building blocks, such as convolution layers, pooling layers, and fully connected layers. A typical architecture consists of repetitions of a stack of several convolution layers and a pooling layer, followed by one or more fully connected layers.

The step where input data are transformed into output through these layers is called forward propagation. Although convolution and pooling operations described in this section are for 2D-CNN, similar operations can also be performed for three-dimensional (3D)-CNN.

3.5.1 Convolutional layer

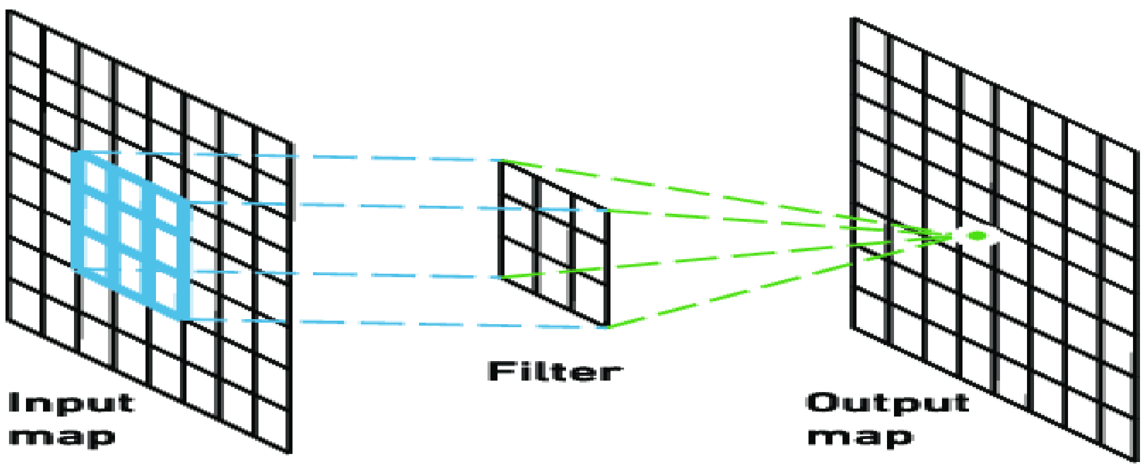

Figure 3.1: Outline of the convolutional layer.

It is the first layer that filters out the entered images. It captures color, edges, gradient direction, and other features so that it is special [58].

Layer parameters consist of a group of learnable filters, which have a small reception field, but it does rely on spanning through the full depth of the input size. During forward scrolling, each filter is grouped across the width and height of the input size, calculating the point product between filter entries and inputs and producing a 2 dimensional activation map for this filter. As a result, the network recognizes filters that are active when it detects a specific type of feature in a spatial location in the CPU [59].

3.5.2 Pooling layer

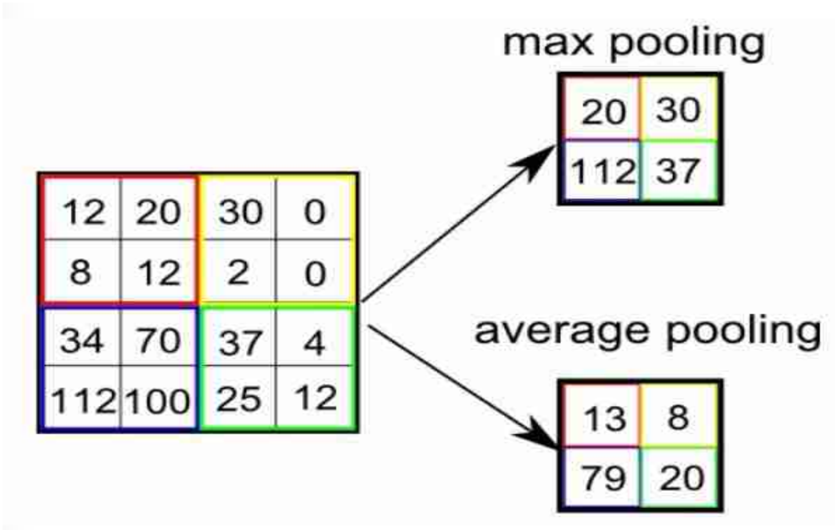

Figure 3.2: Example of two types of Pooling

This layer is usually added after the convolutional layer.It is a form of non-linear lower sampling. There are two types of grouping:

The most common assembly is most common. It divides the input image into a set of non-overlapping rectangles, and outputs the maximum for each sub-region

Average Pooling This type of aggregation is the average value of the portion of the image covered by the core.

3.5.3 Fully connected layer

The conductive layer is completely similar to the method of a neuron Arranged in a conventional neural network. Therefore, every node Its fully connected layer is directly connected to each node in All from the previous layer, from This shape we can notice that all nodes in the last frames in the assembly layer is related as a vector to the first layer of fully connected layer. These are most of the parameters used with CNN is within these layers, and is time-consuming to train .

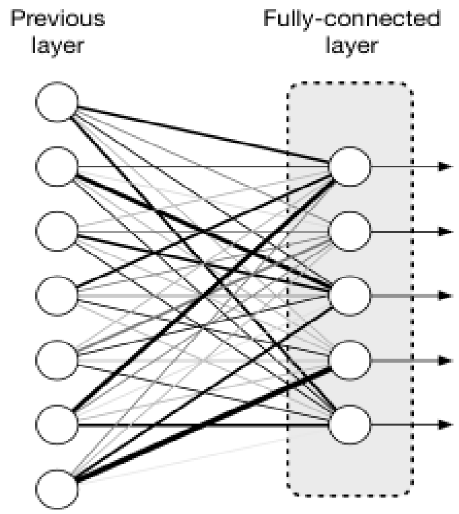

Figure 3.3: Example of two types of Pooling

The main disadvantage of the fully connected layer is that it includes a lot of parameters that need complex calculations in Training examples. Therefore, we are trying to delete a number Nodes and Connections. Nodes can be removed and contacted Satisfied with the Leakage Technology.

3.5.4 Loss layer

The ”loss layer” defines how the training penalizes the deviation between the expected (output) and the real nomenclature and is usually the final layer of the neural network. Different loss functions suitable for different tasks can be used. The loss is used to predict a single class. The Euclidean loss is used to revert to posters of true value

3.5.5 Weights

Each neuron in a neural network computes an output value by applying a specific function to the input values coming from the receptive field in the previous layer. The function that is applied to the input values is determined by a vector of weights and a bias (typically real numbers). Learning, in a neural network, progresses by making iterative adjustments to these biases and weights [60]. The vector of weights and the bias are called filters and represent particular features of the input (e.g., a particular shape). A distinguishing feature of CNNs is that many neurons can share the same filter. This reduces memory footprint because a single bias and a single vector of weights are used across all receptive fields sharing that filter, as opposed to each receptive field having its own bias and vector weighting.

3.6 Choosing hyperparameters

Classification of images is an important task in computer vision involve a large area of applications such as object discovery, localization, and image segmentation . Most adopted Image classification methods are based on deep nerves network and especially CNN. These deep networks have proven to be impressive and sometimes human competitive outcomes . There are several parameters that depend on it:

3.6.1 Number of filters

Because the size of the feature map decreases with depth, layers closer to the input layer will tend to have fewer filters while higher layers can contain more. To balance the calculation at each layer, the product of parameter values is kept with the pixel placement nearly constant across the layers. Preserving more information about the entry re quires maintaining the total number of non-decreasing activation from layer to layer.

3.6.2 Filter shape

The shapes of the common filters found in the literature vary greatly and are usually chosen based on the data set. Thus, the challenge is to find the right level of detail to create abstractions of the appropriate scale, in light of a given data set, and without fatigue.

3.6.3 Max pooling shape

Typical values are (2×2). Very large input volumes may warrant 4×4 pooling in the lower layers. [61] However, choosing larger shapes will dramatically reduce the dimension of the signal and may result in excess information loss. Often, non-overlapping pooling windows perform best.

3.7 Conclusion

CNN is a popular deep learning technique for current visual recognition tasks. Like all deep learning techniques, CNN is very dependent on the size and quality of the training data. Given a well-prepared dataset, CNNs are capable of surpassing humans at visual recognition tasks. However, they are still not robust to visual artifacts such as glare and noise, which humans are able to cope with. The theory of CNN is still being developed and researchers are working to endow it with properties such as active attention and online memory, allowing CNNs to evaluate new items that are vastly different from what they were trained on. This better emulates the mammalian visual system, thus moving towards a smarter artificial visual recognition system.

4

Experimental Results and Discussion

Contents

4.1 Introduction

Human facial image processing has been an active and interesting research issue for years. Since human faces provide a lot of information, many topics have drawn lots of attention and thus have been studied intensively. Most of these are face recognition. Gender prediction system based on facial images has become a wide field. There are many methods that have been proposed in the literature for gender classification. In this chapter. We will see the most important part of the memory, which is representing the results of testing the system in a real environment.

4.2 Working environment

We have used in this work:

- A personal computer Dell Latitude i5 used as a server
- Windows 8.1 Professional
- Processor Intel(R) Core (TM) i5-4310U CPU @ 2.00GHz 2.60GHz
- Installed memory (RAM) 8.00 GB
- System type: 64-bit operating system.

4.3 Development tools

In this part we define the development tools that we are using which are Python and the IDE Pycharm, as we highlight the role of each one as follows:

4.3.1 Python

Python is an interpreted, high-level, and general-purpose programming language. Created by Guido van Rossum and first released in 1991, Python's design philosophy emphasizes code readability with its notable use of significant whitespace. Its language constructs and object-oriented approach aim to help programmers write clear, logical code for small and large-scale projects.

Python is dynamically typed and garbage-collected. It supports multiple programming paradigms, including structured (particularly, procedural), object-oriented, and functional programming. Python is often described as a ”batteries included” language due to its comprehensive standard library. Python interpreters are available for many operating systems. A global community of programmers develops and maintains CPython, a free and open-source reference implementation. A non-profit organization, the Python software foundation, manages and directs resources for Python and CPython development.Below We mention the most important advance and disadvantage of python.

Figure 4.1: Python logo

1. Advantages

   - Easy to Read, Learn, and Write.
   - Improved Productivity.
   - Interpreted Language.
   - Dynamically Typed.
   - Free and Open-Source.

- Huge Libraries Support.
- Portability which means you don't need to change the code to run it on other platforms, with python write once and run it everywhere.

2. Disadvantages

- Difficulty in Using Other Languages.
- Run-time Errors.
- Underdeveloped Database Access Layers.
- Slow Speed.
- Weak in Mobile Computing.

4.3.2 Pycharm

PyCharm is an Integrated Development Environment (IDE) used in computer programming, specifically for the Python language. It is developed by the Czech company JetBrains. It provides code analysis, a graphical debugger, an integrated unit tester, integration with version control systems (VCSes), and supports web development with Django as well as Data Science with Anaconda. We can run PyCharm on Windows, Linux, or Mac OS. Additionally, it contains modules and packages that help programmers develop software using Python in less time and with minimal effort. Further, it can also be customized according to the requirements of developers.

4.4 Gender classification application

To detect gender from the face and observe results , some libraries must be installed first .

4.4.1 Libraries

there are many libraries and packages we have used in this work, but the most important of them are the ones below:

4.4.1.A OpenCV

OpenCV (Open source Computer Vision) is an open source library that contains more than 500 optimized algorithms for image and video analysis [62] . Since its introduction in 1999, it has been largely adopted as the primary development tool by the community of researchers and developers in computer vision.

4.4.1.B Argparse

The argparse module makes it easy to write user-friendly command-line interfaces. The program defines what arguments it requires. The argparse module also automatically generates help and usage messages and issues errors when users give the program invalid arguments.

4.4.1.C Time

This unit provides several functions related to time. For related functionality, see also Date, Time, and Calendar modules. Although this unit is always available, not all functions are available on all platforms. Most of the functions defined in this module call the C library functions on the platform with the same name. Sometimes it can be helpful to refer to the platform documentation, because the connotations of these functions vary by platform.

4.4.2 CNN Architecture

The ResNet convolutional neural network for this python project has 3 convolutional layers:

- Convolutional layer 96 nodes, kernel size 7.
- Convolutional layer 256 nodes, kernel size 5.
- Convolutional layer 384 nodes, kernel size 3.

- Softmax final output layer.

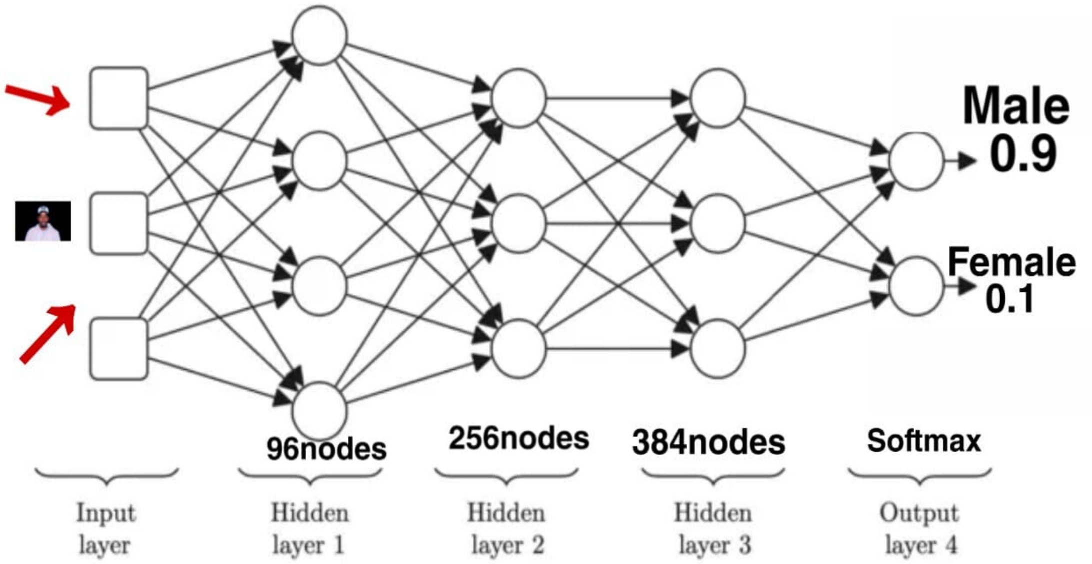

Figure 4.2: Architecture of convolution neural network

To go about the python project, we'll:

- Detect faces.
- Classify into Male/Female.
- Put the results on the image and display it.

4.4.3 Training

In this Python Project, we will use CNN to accurately identify the gender of a person from a single image of a face. We will use the models trained by Tal Hassner and Gil Levi **??**. The predicted gender may be one of 'Male' and 'Female'. because we've faced problems to train the models on our own since we don't have the capable and robust equipment to do such tasks.

4.4.4 Steps of our work

- step 1:

We install all the libraries which we need in our work (OpenCV, Tem, and argparse).

```
import cv2 as cv
import time
import argparse
```

Figure 4.3: Import libraries

- step 2:

At this point, the image is converted into a blob and passed through the grid using the forward function (4.4). The output detections are a 4D matrix, in which the third dimension is duplicated on the detected faces. (Repeats on the number of faces). The fourth dimension contains information about the bounding box and the degree of each face. The output coordinates of the bounding box are normalized between [0,1]. Hence, the coordinates must be multiplied by the height and width of the original image to obtain the correct bounding box for the image.

```
def getFaceBox(net, frame, conf_threshold=0.7):
    frameOpencvDnn = frame.copy()
    frameHeight = frameOpencvDnn.shape[0]
    frameWidth = frameOpencvDnn.shape[1]
    blob = cv.dnn.blobFromImage(frameOpencvDnn, 1.0, (300, 300), [104, 117, 123], True, False)

    net.setInput(blob)
    detections = net.forward()
    bboxes = []
    for i in range(detections.shape[2]):
        confidence = detections[0, 0, i, 2]
        if confidence > conf_threshold:
            x1 = int(detections[0, 0, i, 3] * frameWidth)
            y1 = int(detections[0, 0, i, 4] * frameHeight)
            x2 = int(detections[0, 0, i, 5] * frameWidth)
            y2 = int(detections[0, 0, i, 6] * frameHeight)
            bboxes.append([x1, y1, x2, y2])
            cv.rectangle(frameOpencvDnn, (x1, y1), (x2, y2), (0, 255, 0), int(round(frameHeight/150)), 8)
    return frameOpencvDnn, bboxes
```

Figure 4.4: Face detection codes

- step 3:

We initialize a Model and Prototype. A model tends to lend itself to the aesthetics side of things, used to demonstrate look and feel. A Prototype is more geared towards testing to see if the final piece will work as intended. Whether that is its physical size, geometry, or function. (See Figure 4.5).

```
faceProto = "opencv_face_detector.pbtxt"
faceModel = "opencv_face_detector_uint8.pb"


genderProto = "gender_deploy.prototxt"
genderModel = "gender_net.caffemodel"
```

Figure 4.5: Trained Models

- step 4:

We use the (readNet ()) as figure 4.6 method to upload facial recognition, the gender discrimination network. The first parameter holds the trained weights and the second holds the grid configuration.

```
genderNet = cv.dnn.readNet(genderModel, genderProto)
faceNet = cv.dnn.readNet(faceModel, faceProto)
```

Figure 4.6: ReadNet method for network reading

- step 5:

We feed the input by opening the webcam, and give the network a forward pass to gain the confidence of the two groups. Whichever is higher, this is the gender of the person in the photo.

- step 6:

We will display the output of the network on the input images and show them using the imshow function (See figure 4.7).

```
label = "{}".format(gender)
cv.putText(frameFace, label, (bbox[0], bbox[1]-10), cv.FONT_HERSHEY_SIMPLEX, 0.8, (0, 255, 255), 2, cv.LINE_AA)
cv.imshow(" Gender Demo", frameFace)
```

Figure 4.7: Output method using the imshow function

4.5 Real-time test of sofware

We will present a set of results that we have made in the experience of our special program by facing the webcam of the PC and we have only one example of a female. Below the results show that the network gives satisfy performance when the person is facing directly the webcam.

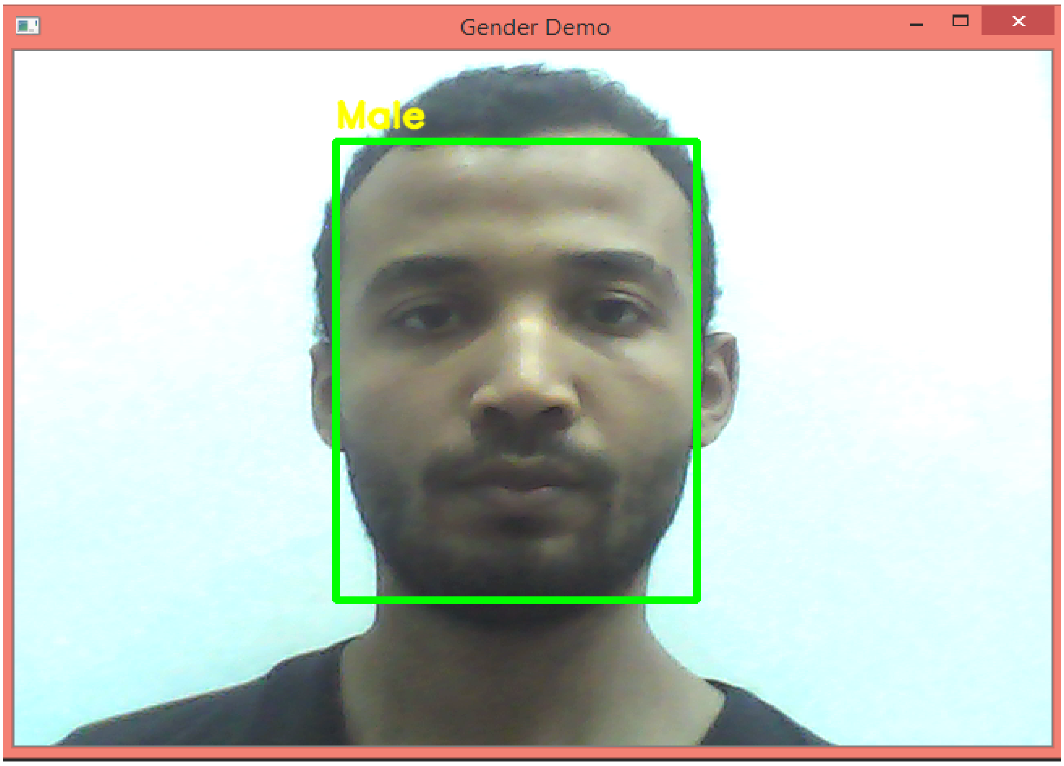

Figure 4.8: The result of the first test

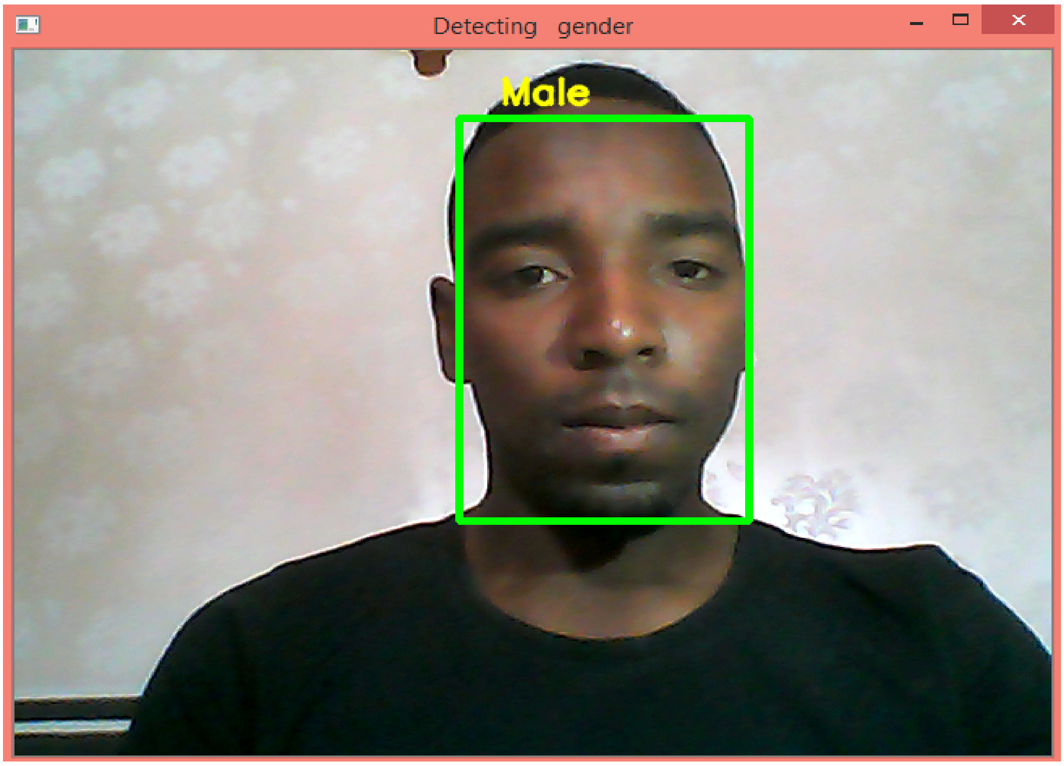

Figure 4.9: The result of the second test

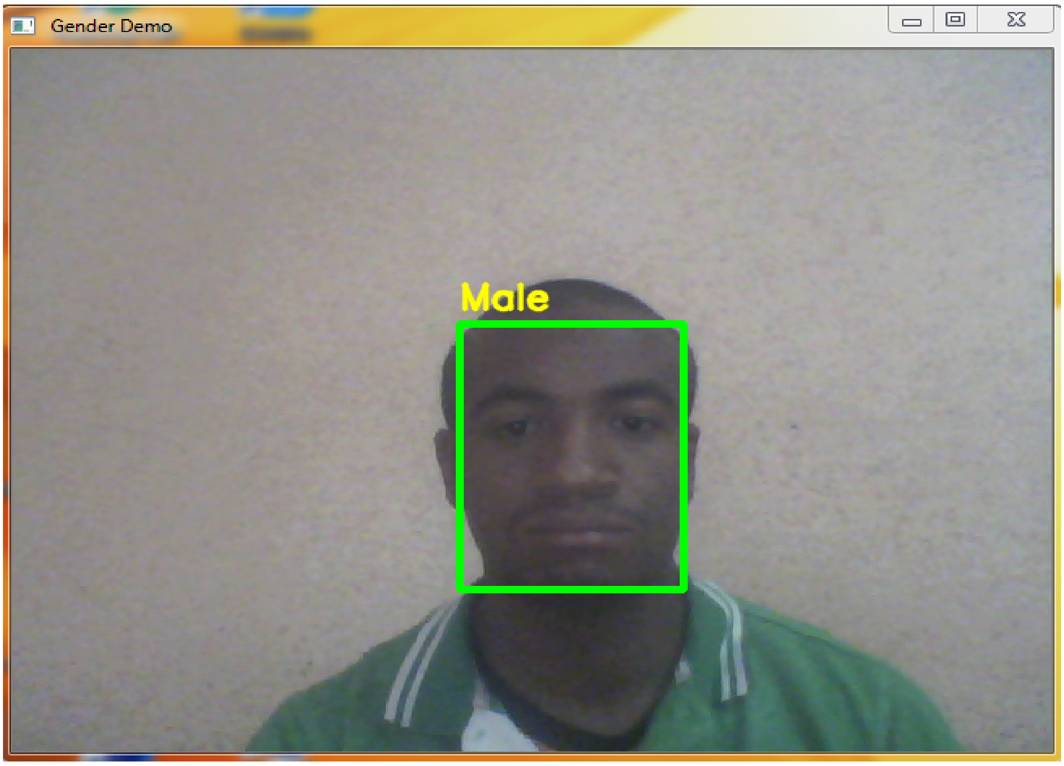

Figure 4.10: Third test result

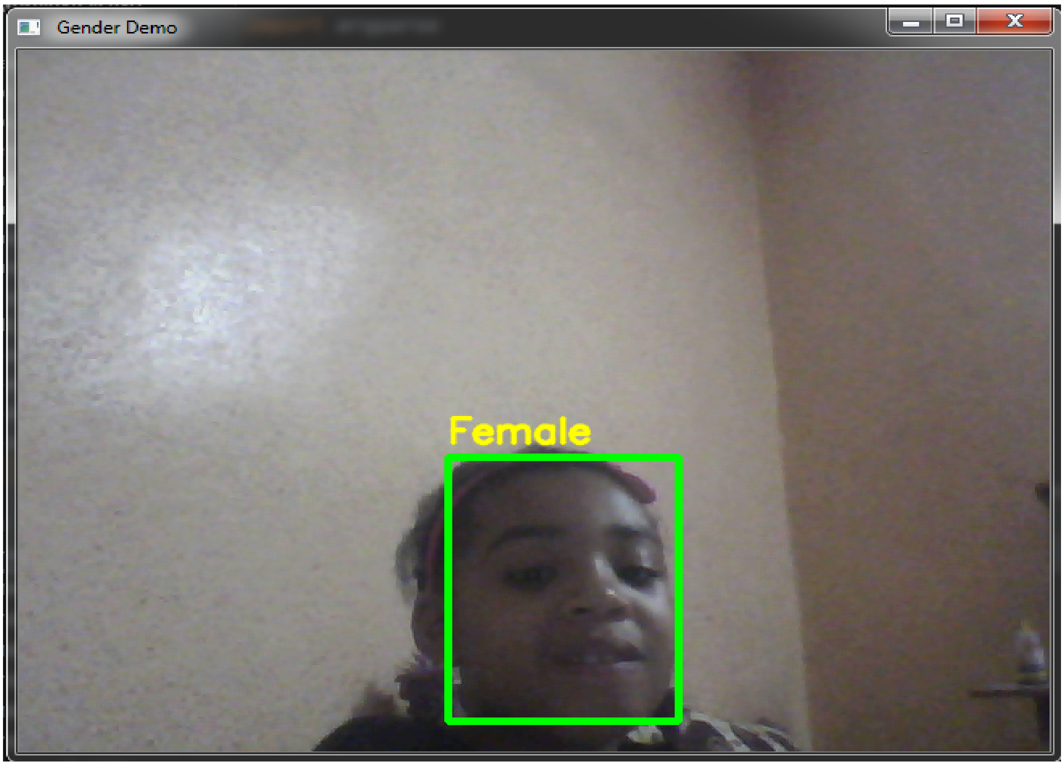

Figure 4.11: Fourth test result

4.6 Conclusion

At the end of this chapter, we've got almost a complete understanding of our application by the realization steps. And we have explained the efficiency and importance of our project through the experiments we have done. And finally, we can say that we have achieved our goals. And the results we have obtained are encouraging and satisfying.

General Conclusion

Automatic gender recognition has become now an important requirement due to its usage in various software and hardware, particularly because of the growth of online social networking websites and social media. And among the many methods that used for that purpose CNN network.

In this memory , we have studied a CNN technique that can tell the gender of person according to his face . In the first part of the memory , we have explored the topic of soft biometrics and its types, we have seen also how to use the CNN network to differentiate between genders depending on a database . In the last chapter , we have examined a real time gender classification application that uses a trained models based on database using CNN network . Gender is a very sensitive topic nowadays and researches on this topic are still continued since there is a lot of challenges .

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