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Identifying Gender from Images of Face

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Abstract: The main objective of this project is to classify the gender based on different facial features such as eyes, nose, mouth, overall features such as face contour, head shape, hair line etc. The gender classification algorithm uses machine learning technique (supervised learning). In this case the algorithm is trained on a set of male and female faces and then used to classify new data. In this project, face detection and gender classification methods are combined. The face detection acts as a pre-processing operation to the gender classifier that determines the gender.There are multiple methods in which facial recognition systems work, but in general, they work by comparing selected facial features from a given image with faces within a database. It is also described as a Biometric Artificial Intelligence based application that can uniquely identify a person by analyzing patterns based on the person's facial textures and shape.Automated gender recognition plays an important role in many application areas such as human computer interaction,biometric, surveillance, demographic statistics etc.
Keywords: Machine learning, Supervised learning, Open CV, Python, CNN classification

I. INTRODUCTION

Gender is one of the main factors in the interaction between individuals. Recently, with the development of social media environments and smartphones, gender recognition applications have both begun to grow and become important. In many fields such as face recognition, facial expression analysis, tracking and surveillance, human-computer interaction, biometric, gender recognition applications can be seen. In this project, gender recognition was carried out from face images with deep learning. Face is one of the most important biometric traits. Face recognition is one of the most flourishing applications of image analysis and has gained popularity in the past several decades. There are many existing methods for face recognition. The main motive of this project is to classify the gender based on different facial features such as eyes, nose, mouth, overall features such as face contour, head shape, hair line etc. The gender classification algorithm uses machine learning techniques (supervised learning) and CNN which makes gender recognition more efficient when compared to other methods.

II. LITERATURE SURVEY

There have been several papers over the years studying the topic of gender classification. Almost all of the work in gender classification involves extracting features from faces and classifying those features using labeled data. They mostly differ in the way these two steps are performed. Therefore, gender classification approaches can be categorized based on the feature extraction and classification methods. Feature extraction can be broadly categorized into a) Appearance- based methods, and b) Geometry-based methods. In appearance-based methods the whole image is considered rather than local features that are present in different parts of the face. On the other hand, in geometry-based approaches, the geometric features (e.g. distance between eyes, face width, length, thickness of nose, etc.) of a face are considered. In this section, only the works related to appearance-based approaches are discussed. For the case of classification, most of the works use neural networks, discriminant analysis, nearest neighbors, and SVMs.Early works in gender classification mostly used neural networks with face image as raw input. Some of these are Golomb et al.'s two-layer network called sexnet, Tamura et al.'s multilayer neural network, etc. Gutta et al. takes a hybrid approach using neural networks and decision trees.

Moghaddam et al. uses non-linear SVMs to classify faces from low-resolution "thumbnail" images of size 21-by-12. The authors also experimented with other types of classifiers including different types of RBFs, Fisher's linear discriminant, Nearest Neighbor, and Linear classifier. For SVM they looked at Gaussian RBF kernel and cubic polynomial kernels. They used a total of 1,755 thumbnails (1,044 males and 711 females) and reported the error rate of performing five-fold cross-validation. The best result was obtained for SVM with the Gaussian RBF kernel which had an overall error rate of 3.38%, for males and females' error rates were 2.05% and 4.79% respectively.Jain et al. in presents an approach using ICA and SVM. They studied the performance of different classifiers namely- cosine classifier that finds the distance between two features lying on an hyper-sphere surface, linear discriminant classifier that finds the projection of the input image maximizing the ratio of the between-class scatter and within class scatter, and SVM which finds the maximal separating hyper-plane between the male and female features.

A training set of 200 images out of a database of size 500 was used in their work. Using ICA 200 independent components were determined from the training set.They also experimented with different sizes of training set. In their work, SVM performed constantly well with respect to the other classifiers. The best performance they got was 95.67% using ICA and SVM for a training set of size 200.

III. METHODOLOGY

Fig.1 Block Diagram

1) *Sensing:* The first step of gender classification is to obtain the effective raw data using specific sensors including camera, recorder, physiological instrument, social networks based information etc. Based on the acquired features, various approaches are employed to perform gender classification.
2) *Preprocessing:* Pre-processing is a necessary procedure to improve the quality of raw data, which includes normalization of the main signal detection, the extraction of the informative area and the correction of imperfections such as filing holes, noise removal, face detection, etc. With the appropriate signal pre-processing procedure the undesired information is eliminated from the raw information and has few effects on the quality of the feature extraction, leading to the improvement in the identification accuracy rate.
3) *Feature Extraction:* Feature extraction captures the main characters of the pre-processed signal as the input parameter for classification algorithm. The feature extraction module minimizes the size of data by extracting the features of the pre-processed information that are useful for classification. The desired features should be easily computed, robust, distinctive and insensitive to various conditions. In the next phase, the classifier will process the extracted features and perform the classification.
4) *Classification Algorithm:* The classification algorithm is the core of gender identification. Generally, classification approaches can be classified into two categories: appearance based and non appearance based approaches. The appearance based approach is using a static image or an animated video to conduct gender classification. The non appearance based approach classifies the gender by analyzing the person's physical, biometric, or social network based information. Among these two approaches, several types of classifiers have been utilized for gender classification, such as support vector machine (SVM) , k-nearest neighbors (KNN), and Gaussian mixture models (GMM). The choice of classification algorithm is crucial depending on each case in order to achieve higher identification accuracy.
5) *Evaluation:* In this step some measures are used to assess the performance of the gender classification system. Basically, the system is tested in terms of accuracy, trustworthiness.

IV. PROPOSED METHOD

A. CNN Algorithm

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics.The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlap to cover the entire visual area.

The convolutional neural network for this project has 3 convolutional layers:
1) Convolutional layer; 96 nodes, kernel size 7
2) Convolutional layer; 256 nodes, kernel size 5
3) Convolutional layer; 384 nodes, kernel size 3

It has 2 fully connected layers, each with 512 nodes, and a final output layer of SoftMax type.

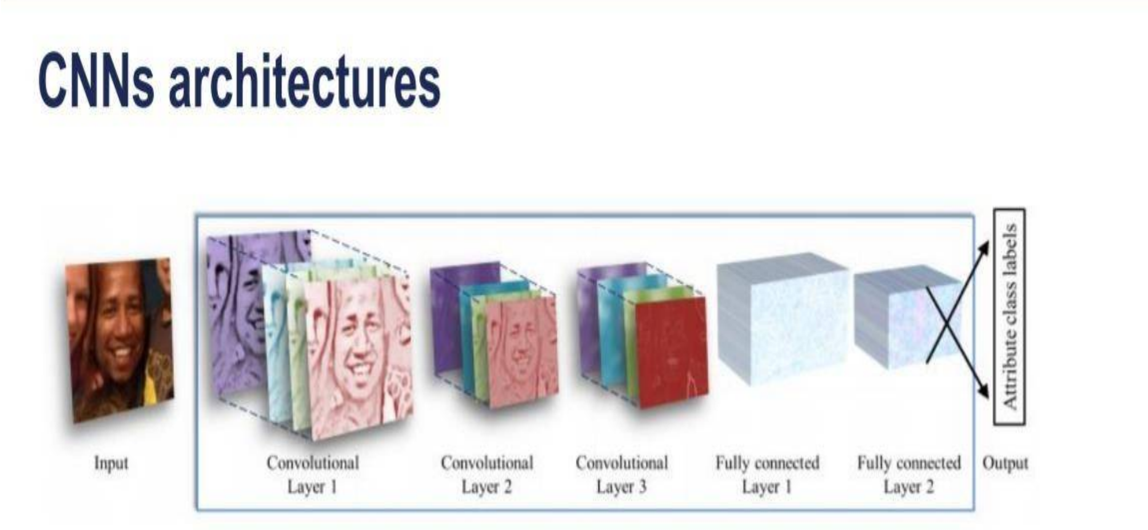

Fig.2 CNN Architectures.

a) The first layer is responsible for capturing low level features such as color, gradient, orientation etc. The layers 2 and 3 makes the architecture adapt to high level features and network will get wholesome understanding of images in the data set. The convolution operation is the extraction of high-level features.

b) The element involved in carrying out the convolution operation in the first part of a convolutional layer is called kernel. The kernel size refers to the width and height of the filter mask. Each kernel has its own bias.

c) The max pooling layer returns the pixel with maximum value from the set of pixels within the kernel. The fully connected layer is a feed forward neural network forms the last few layers in the network. The input to the fully connected layer is the output of final pooling or from convolutional layers which is flattened and then sent into the fully connected layer.

d) The flattened output is fed to a feed forward neural network and back propagation is applied to every iteration of training. The model is able to distinguish between dominating and low-level features and classify them using SoftMax technique. SoftMax activation function is used to get the probabilities of the input being in a particular class.

- *Dataset:* We have used Adience dataset which is available in public domain. This dataset serves as a benchmark for face photos. It also includes various real-world imaging conditions like noise, lighting, pose and appearance. Images have been collected from "Flickr" albums. It has total of 26,580 photos of 2,284 subjects and is about 1GB in size. The model has been trained on this dataset.
- *Argparse Library:* To get an image as argument from the user, the developer should use an argument parser. Initialize the protocol of buffer and model. Mean values of the gender are also initialized to classify the data. We use the argparse library to create an argument parser so we can get the image argument from the command prompt. We make it parse the argument holding the path to the image to classify gender and age for.
- *CAFFEMODEL:* Caffe is a deep learning framework made with expression, speed and modularity in mind. It has an expressive architecture which encourages application and innovation. Extensible code which fosters active development. Speed makes Caffe perfect for research experiment and industry development.
- *Shallow Copy And Blob:* A BLOB (large binary object) is a MySQL data type that can be used to store binary data. We can convert our files and images into binary data in Python and store them in MySQL table using BLOB.A shallow copy means constructing a new collection object and then populating it with references to the child objects found in the original. In essence, a shallow copy is only one level deep. The copying process does not recurse and therefore won't create copies of the child objects themselves.The face detector creates a shallow copy of the image and stores the height and width. It further creates a BLOB from the shallow copy.

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B. GUI Design

Fig.2 GUI Design.

1) Initialize the protocol buffer and the required buffer model.
2) readNet() method is used to load the networks. The first parameter holds trained weights and the second carries network configuration.
3) We need to capture the video stream to classify on a webcam or we can pass an image file as input through command line arguments.
4) Now until any key is pressed, we read the stream and store the content into the names hasFrame and frame. If it isn't a video, it must wait, and so we call up waitKey() from cv2, then break.
5) But if there are indeed faceBoxes, for each of those, we define the face, create a 4- dimensional blob from the image. In doing this, we scale it, resize it, and pass in the mean values.
6) We feed the input and give the network a forward pass to get the confidence of the two classes. Whichever is higher, that is the gender of the person in the picture.

We'll add the gender to the resulting image and display it with imshow().

V. RESULTS

1) Test Input 1

py gad.py --image kid1.jpg

2) Output 1

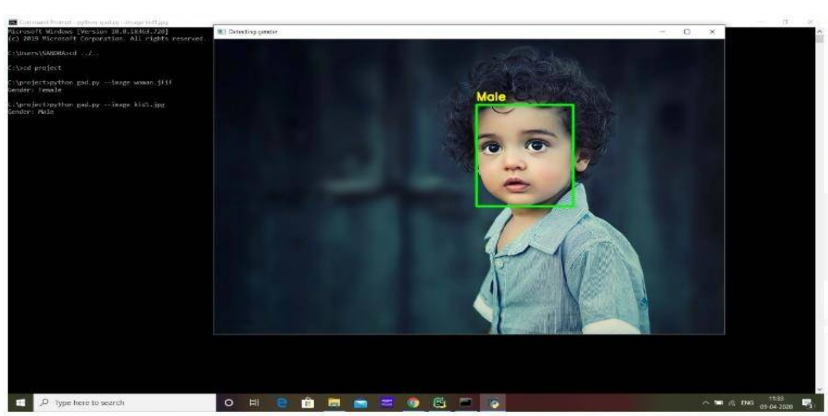

Fig.3 Output1

VI. CONCLUSION AND FUTURE WORK

In this python project, we have implemented the general system to detect gender from a picture of a face with a decent accuracy rate. The gender identification method uses preprocessing, face detection, feature Extraction and then classification. The project's objective was to develop a gender recognition system implementing the computer visions and enhancing the advanced feature extraction and classification in gender recognition. The computational models, which were implemented in this project, were chosen after extensive research, and the successful testing results confirm that the choices made by the researcher were reliable. We used CNN model in this project . The authors reported 96.2% correct recognition on ORL database of 400 images of 40 individuals. This system was tested under very robust conditions in this experimental study and it is envisaged that real-world performance will be far more accurate. The fully automated face detection and recognition system was not robust enough to achieve a high recognition accuracy.

The Present model can be enhanced through some extended features. We have to work on performance when there are multiple images and recognize third gender accurately. If a gender recognition system can reduce the number of images that a human operator has to search through for a match from 10000 to even a 100, it would be of incredible practical use in law enforcement. The automated gender recognition systems implemented in this thesis did not approach the performance, nor were that robust as a human's innate recognition system. However, it gives an insight into what the future may hold in computer vision. This can be used in many applications, such as face recognition, gender recognition and age estimation. The value of these applications depends in several areas, such as security applications, law enforcement applications, and attendance systems.

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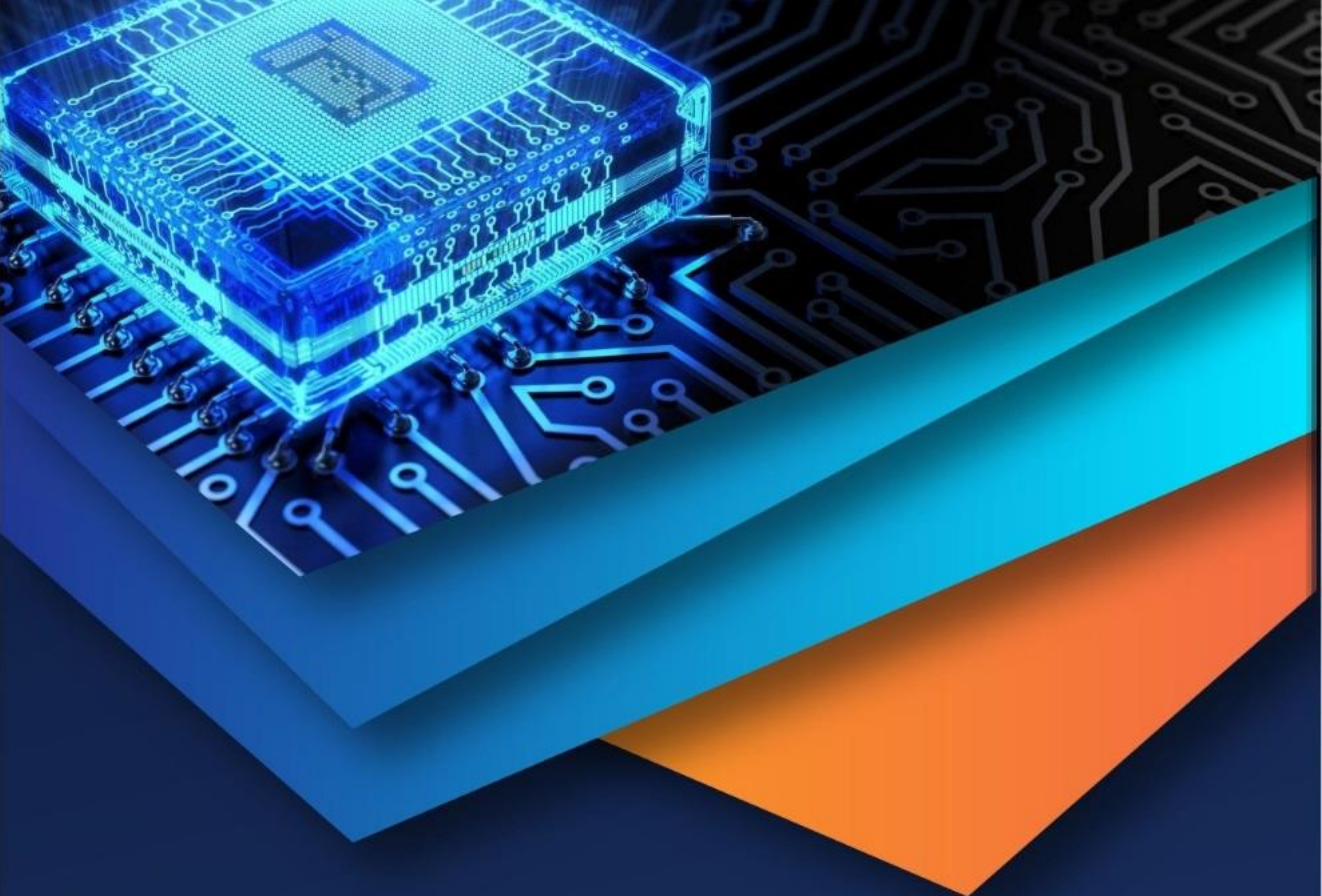

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