

Face Recognition Using Semantic Assisted Convolutional Neural Networks

Kalyani D Sonawane¹, Dr. Sudhir D. Sawarkar², Prof. Archana Gulati³

¹Student of Master of Computer Engineering

²Principal Of Datta Meghe College of Engineering, Airoli, Navi Mumbai

³Assistant Professor of Computer Engineering, Datta Meghe College of Engineering, Airoli

Corresponding Author: Kalyani D Sonawane

ABSTRACT:- In today's age of automation; face recognition is a vital component for authorization and security. The principal aim of facial analysis is to extract valuable information from face images, such as its position in the image, facial characteristics, facial expressions, the person's gender or identity. It has received substantial attention from researchers in various fields of science such as biometrics and computer vision. In this paper, we present the problem of automatic appearance-based facial analysis with machine learning techniques and describe common specific sub-problems like face detection, facial feature detection and face recognition which are the crucial parts of many applications in the context of indexing, surveillance, access-control or human-computer interaction. To tackle this problem, we particularly focus on a technique called Convolutional Neural Network (CNN) which is inspired by biological evidence found in the visual cortex of mammalian brains and which has already been applied to many different classification problems. Our framework, referred to as semantics-assisted convolutional neural networks (SCNNs), incorporates explicit semantic information to automatically recover comprehensive face features. The proposed system is a new framework to efficiently and accurately match face images that are automatically acquired under less-constrained environments. The paper refers to semantics-assisted convolutional neural networks (SCNNs), incorporates explicit semantic information to automatically recover comprehensive face features.

KEYWORDS:- Face Recognition, Artificial Neural Neuron Architecture, Neural Network, CNN, SCNN

Date of Submission: 21-05-2018

Date of acceptance: 05-06-2018

I INTRODUCTION

The automatic processing of images to extract semantic content is a task that has gained a lot of importance during the last years due to the constantly increasing number of digital photographs on the Internet or being stored on personal home computers. The need to organize them automatically in an intelligent way using indexing and image retrieval techniques requires effective and efficient image analysis and pattern recognition algorithms that are capable to extract relevant semantic information. Especially faces contain a great deal of valuable information compared to other object or visual items in images. For example, recognizing a person on a photograph, in general, tells a lot about the overall content of the picture. In the context of human-computer interaction (HCI), it might also be important to detect the position of specific facial characteristics or recognize facial expressions, in order to allow, for example, a more intuitive communication between the device and the user or to efficiently encode and transmit facial images coming from a camera. Thus, the automatic analysis of face images is crucial for many applications involving visual content retrieval or extraction. The principal aim of facial analysis is that to extract valuable information from face images, such as its position in the image, facial characteristics, facial expressions, the person's gender or identity. Advances in face recognition have come from considering various aspects of this specialized perception problem.

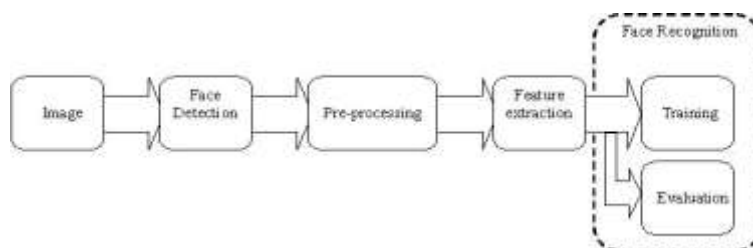


Fig.1 Face Recognition System

II NEURAL NETWORKS

Many pattern recognition problems like object recognition, character recognition, etc. have been faced successfully by neural networks. These systems can be used in face detection in different ways.

The simplest definition of a neural network, more properly referred to as an 'artificial' neural network (ANN), is provided by the inventor of one of the first neurocomputers, Dr. Robert Hecht-Nielsen. Artificial neural networks (ANNs) or connectionist systems are computing systems vaguely inspired by the biological neural networks that constitute animal brains. Such systems "learn" (i.e. progressively improve performance on) tasks by considering examples, generally without task-specific programming.

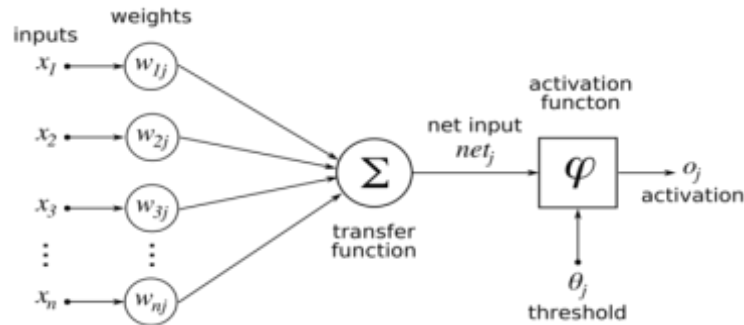


Fig.2 Artificial Neuron Architecture

An ANN is based on a collection of connected units or nodes called artificial neurons (a simplified version of biological neurons in an animal brain) as shown in Figure2. Each connection (a simplified version of a synapse) between artificial neurons can transmit a signal from one to another. The artificial neuron that receives the signal can process it and then signal artificial neurons connected to it as shown in Figure2.

III CONVOLUTIONAL NEURAL NETWORKS

Deep learning is learning multiple levels of representation and abstraction, helps to understand the data such as images, audio and text. The concept of Deep Learning comes from the study of Artificial Neural Network; Multilayer Perceptron which contains more hidden layers is a Deep Learning structure. Feed-forward neural network or Multilayer Perceptron with multiple hidden layers in artificial neural networks is usually known as Deep Neural Networks (DNNs). Convolutional Neural Networks (CNN) is one kind of feed-forward neural network. A convolutional neural network is a deep learning algorithm that is used in object recognition. CNN is a biologically inspired variant of multilayer Perceptron (MLP) and well known as one of typical deep learning architectures. CNN has shown strong ability to learn effective feature representation from input data especially for image/video understanding tasks, such as handwritten character recognition, large-scale image classification, face recognition, etc.

Convolutional neural networks (CNNs) are composed of a hierarchy of units containing a convolutional, pooling (e.g. max or sum) and non-linear layer (e.g. ReLU $\max(0, x)$). In particular, unlike a regular Neural Network, the layers of a ConvNet have neurons arranged in 3 dimensions: width, height, depth. (Note that the word *depth* here refers to the third dimension of an activation volume, not to the depth of a full Neural Network, which can refer to the total number of layers in a network.)

The three basic components to define a basic convolutional network:

1. The convolutional layer
2. The Pooling layer
3. The output layer

The architecture of CNN is given as follows:

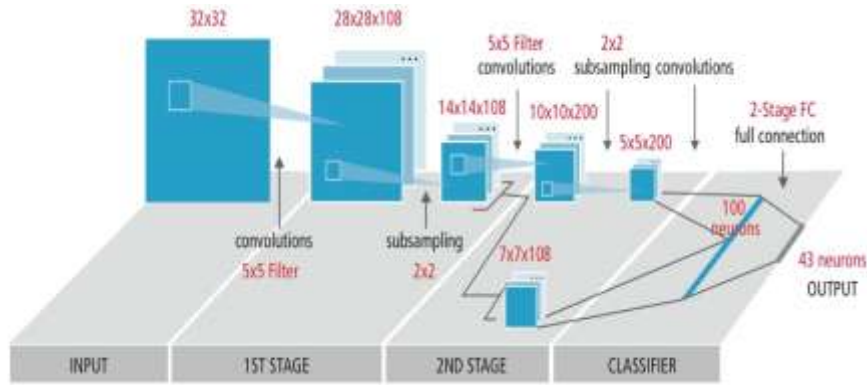


Fig.3 Architecture of CNN

A. Convolutional Layer

The convolution operation extracts different features of the input. The first convolution layer extracts low-level features like edges, lines, and corners. Higher-level layers extract higher-level features. ConvNets derive their name from the “convolution” operator. The primary purpose of Convolution in case of a ConvNet is to extract features from the input image. Convolution preserves the spatial relationship between pixels by learning image features using small squares of input data

B. RELU

An additional operation called ReLU has been used after every Convolution operation. ReLU stands for Rectified Linear Unit and is a non-linear operation. ReLU is an element wise operation (applied per pixel) and replaces all negative pixel values in the feature map by zero.

C. Pooling

Spatial Pooling (also called subsampling or downsampling) reduces the dimensionality of each feature map but retains the most important information. Spatial Pooling can be of different types: Max, Average, Sum etc. In case of Max Pooling, we define a spatial neighborhood (for example, a 2x2 window) and take the largest element from the rectified feature map within that window.

D. Fully connected/output layer

The Fully Connected layer is a traditional Multi Layer Perceptron that uses a softmax activation function in the output layer (other classifiers like SVM can also be used, but will stick to softmax in this post). The term “Fully Connected” implies that every neuron in the previous layer is connected to every neuron on the next layer

IV SEMANTIC ASSISTED CONVOLUTIONAL NEURAL NETWORKS

Semantic Face Retrieval refers to retrieval of face images based on not the raw image content but the semantics of the facial features like description of the nose or chin of a person. For Instance “A round faced person with blonde hair and mustache” is a verbal semantic description of a face. It must be noted that there exist many mug-shot retrieval systems that retrieve face images based on user’s choice of similar faces from a pool of face images. Our approach for face recognition using SCNN does not require training samples from target datasets, while achieving outperforming results, which is a key advantage over state-of-the-art approaches and . In our experiments, the SCNN is trained with one database and tested on totally independent/separate databases. The testing and training sets have mutually exclusive subjects and highly different image quality as well as imaging conditions and/or equipment’s. Our approach quickly narrows down the possible images from a large database of images based on matching verbal description of the face with the tagged description of the faces in the database. Thus the system can be used as a first step in a search process and all further searches can be performed on the smaller set of images retrieved by the system for obtaining more accurate results efficiently.

As from below Figure3, we simply add a branch, which is also a CNN, to the existing CNN. The attached CNN is not trained using the identity of the training data but the semantic groups. For example, we could train CNN2 using the gender information of the training sample, i.e., let the CNN2 be able to estimate the gender instead of identity, and train CNN3 using the ethnicity information. After the CNNs are trained, we can combine the output of each CNN in the way of feature fusion. We refer to such extended structure of the CNN as Semantics-Assisted CNN (SCNN for short).

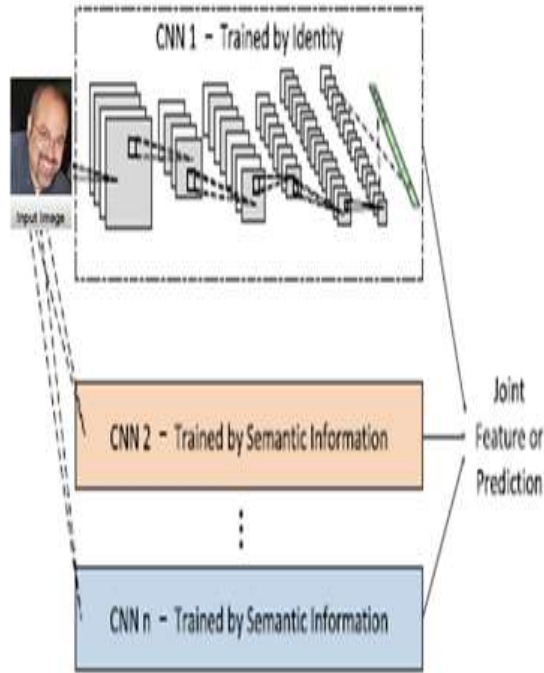


Fig.4 Face Recognition using SCNN

V ANALYSIS

Table I: Comparative Analysis for NN,CNN,SCNN

Factors	NN	CNN	SCNN
Efficiency	Medium	More	High
Accuracy	Good	Better	Best
Speed	Slow	Fast	Fast
Complexity	High	Less	Less
Training Samples	Large number	Large number	Less number
Affordability	Not afforded easily	Possible	Easily afforded

The Comparative analysis is done by studying Neural Networks, Convolutional Neural Networks and Semantic Convolutional Neural Networks in which the performance of SCNN is better compared to CNN and NN. As well the above table shows the accuracy rate of SCNN is best. Due to storage of Semantic information for face recognition the speed required to train the samples is less comparable to CNN and NN. Hence SCNN provides better results to face recognition.

VI CONCLUSIONS

Face recognition might be a very easy task for human beings, but it is extremely difficult to make a machine detect and recognize human faces. In this work it has been shown that if a facial image of a person is given then the network can able to recognize the face of the person. The whole work is completed through the following steps: Facial image of a person has been collected by taking three different samples of the person for the experiment.

In particular, we proposed a robust and more accurate framework for the face recognition using the semantics-assisted convolutional neural network (SCNN). By training one or more branches of CNNs with semantically information corresponding to training data, the SCNN is capable of recovering more comprehensive features from the images and therefore achieve superior performance. SCNN is capable of recovering more comprehensive features from the images and therefore achieve superior performance. The performance and hence, the efficiency of the network can be increased. This technique approach is better in performance over other techniques due to high accuracy rate for complex face recognition, adaptive learning as well as better tolerance factor to fault even though more time may be required to train the networks. However, it is believed that a well-designed network structure may explicitly incorporate semantic information itself and facilitate efficient training in an end-to-end training manner.

REFERENCES

- [1]. Thai Hoang Le, "Applying Artificial Neural Networks for Face Recognition",2011
- [2]. Ernst Kussul, Tetyana Baydyk, "Face Recognition Using Special Neural Networks",2015
- [3]. Md. Zahangir Alom, Paheding Sidike, Vijayan K. Asari, Tarek M. Taha, "State Preserving Extreme Learning Machine for Face Recognition",2015
- [4]. Suhas S.Satonkar, Vaibhav M.Pathak, Dr. Prakash B. Khanale, "Face Recognition Using Principal Component Analysis and Artificial Neural Network of Facial Images Datasets",2015
- [5]. Zijing Zhao, Student Member, IEEE, and Ajay Kumar, Senior Member, IEEE, "Accurate Periocular Recognition Under Less Constrained Environment Using Semantics-Assisted Convolutional Neural Network",2016
- [6]. Bong-Nam Kang, Yonghyun Kim, y and Daijin Kim, "Deep Convolution Neural Network with Stacks of Multi-scale Convolutional Layer Block using Triplet of Faces for Face Recognition in Wild",2016
- [7]. L. Nie, A. Kumar, and S. Zhan, "Periocular recognition using unsupervised convolutional RBM feature learning," in Proc. 22nd Int. Conf. Pattern Recognit. (ICPR), Stockholm, Sweden, Aug. 2014
- [8]. Aruni RoyChowdhury Tsung-Yu Lin Subhransu Maji Erik Learned-Miller, "One-to-many face recognition with bilinear CNNs" ,2016
- [9]. Jianxin Wu, "Introduction to Convolutional Neural Networks"

Kalyani D Sonawane. "Face Recognition Using Semantic Assisted Convolutional Neural Networks." *International Journal Of Engineering Research And Development* , vol. 14, no. 05, 2018, pp. 61–65