

Performance Analysis of Semantic Assisted Convolutional Neural Networks in Face Recognition

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Abstract : In today's age of automation, face recognition is a vital component for authorization and security. It has received substantial attention from researchers in various fields of science such as biometrics and computer vision. Recently, deep convolutional neural networks have set a new trend in fields of face recognition by improving the state-of-the-art performance. By using deep neural networks, much more sophisticated and high level abstracted features can be learned automatically. In this paper, we propose a method for face recognition using semantic assisted convolutional neural network.(SCNN) . Our framework, referred to as SCNNs, incorporates explicit semantic information to automatically recover comprehensive face features. We demonstrate the performance of the SCNN model beginning from CNN basics. We then show results for face analysis using an external database with respect to existing systems basically NN and CNN. The results of the proposed approach were very encouraging and demonstrate superiority when compared with other techniques.

Keywords – Face Recognition, NN, CNN, SCNN, Comparative Analysis

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I. INTRODUCTION

Face recognition is hugely used in biometric systems. It is also useful in human computer communication, computer operated reality, database retrieval, multimedia, computer entertainment, information security operating system, medical records, online banking. Biometric personal identification passports, driver licenses, automated identity verification border controls, law enforcement video surveillances, investigation, personal security driver monitoring system, home video surveillance system. Face recognition in unconstrained environments is very challenging problem in computer vision tasks. In the past two decades, a large number of methods were proposed to tackle the face recognition to be robust to illumination condition, pose variation, and facial expression.

Deep learning is a concept that is impacting our daily lives more often. We do not notice it, because deep learning is used in the background of the applications that we use. An example of deep learning that is used in our daily lives is the search algorithm of Google Search.

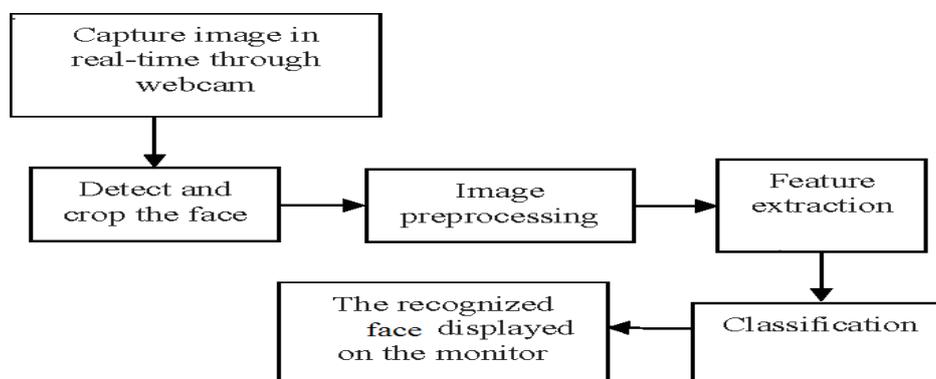


Fig1: Face Recognition System

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. We will outline the most important existing approaches to facial image analysis and present novel methods based on Neural Networks (NN) to detect, normalize and recognize faces and facial features.

II. RELATED WORK

In the recent years, different architectures and models of ANN were used for face detection and recognition. ANN can be used in face detection and recognition because these models can simulate the way neurons work in the human brain. This is the main reason for its role in face recognition. This research includes summery review of the researches related to face detection based on ANN.

1. Neural Networks

Neural network is a very powerful and robust classification technique which can be used for predicting not only for the known data, but also for the unknown data. It works well for both linear and non linear separable dataset. There are three types of neutrons in an ANN, input nodes, hidden nodes, and output nodes

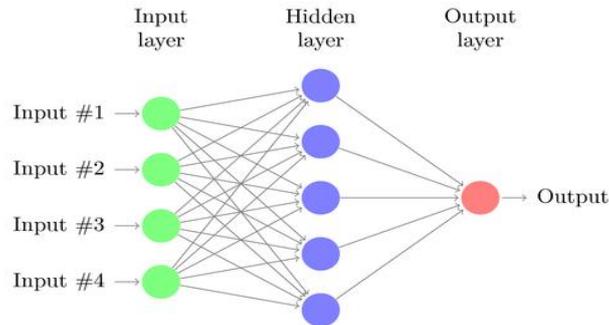


Fig2: Artificial Neural Network Architecture

2. Convolutional Neural Networks

In recent years, Convolutional Neural Network (CNN) has gained popularity for its strong ability to extract comprehensive features from the input data, especially for visual patterns. It has demonstrated its robustness to the real-life intra-class spatial variations. 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 $\max(0,x)$).

Convolutional neural network takes the input image, define a weight matrix and the input is convolved to extract specific features from the image without losing the information about its spatial arrangement. Another great benefit this approach has is that it reduces the number of parameters from the image.

CNN algorithm has two main processes: convolution and sampling: 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 The pooling/sub-sampling layer reduces the resolution of the features. It makes the features robust against noise and distortion. There are two ways to do pooling: max pooling and average pooling. In both cases, the input is divided into non-overlapping two-dimensional spaces. The three basic components to define a basic convolutional network:

- i. The convolutional layer
- ii. The Pooling layer
- iii. The output layer

The architecture of CNN is given as follows:

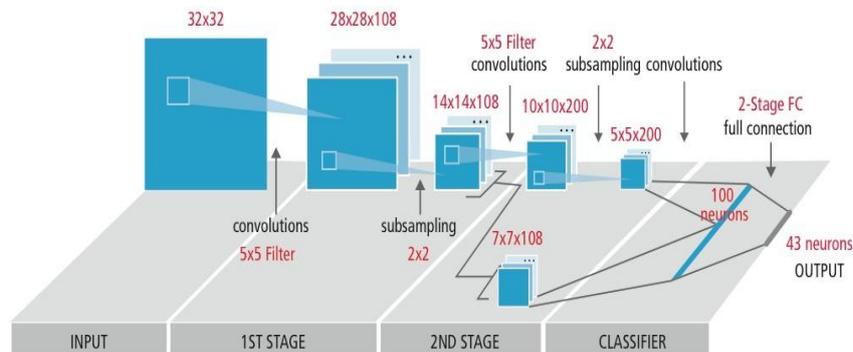


Fig3: Architecture of CNN

Even if the CNN is gives better performance but still it has some limitations. Limitations are as follows:

- i. To achieve superior performance using CNN based methods, a common way is to add more layers to make the network deeper and more comprehensive, and/or devote more labeled training data because CNN is usually trained in a supervised manner.
- ii. Hard to afford to train such deep networks due to the lack of enough
- iii. The network goes deeper; the need for training data grows accordingly computational power.
- iv. It is difficult to acquire enough labeled training samples.
- v. For instance, where the developed CNN is not very deep (nine layers), a total of ~200,000 face images from more than 10,000 people were used for training to achieve superior performance.

Therefore, we are motivated to improve the performance of existing CNN based architecture in another way - to enhance CNN with supervision from explicit semantic information. Hence we have proposed the advance system for face recognition using Semantic assisted Convolutional Neural Networks

III. PROPOSED SYSTEM

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. While these systems do retrieve faces based on semantic descriptions, they do not directly deal with semantically describing the face or retrieving faces according to semantic contents.

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. The SCNN architecture can also enable recovery of more comprehensive periocular features from the limited training samples. Another key advantage of proposed method in this paper is its computational simplicity, *i .e.*, our trained model requires much less computational time for feature extraction and matching compared with other methods. 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 the below Figure4, 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). Despite the simplicity of this idea, it can inherently improve the original CNN by adding more discriminative power to it

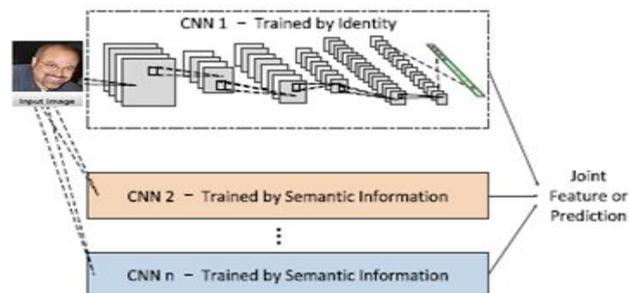


Fig4: Structure of SCNN

The proposed system can be divided into the Enrollment sub-system and the Retrieval subsystem. The Enrollment sub-system accepts as input images that contain frontal view of a face. It in turn outputs semantic descriptions of the face such as whether the person is wearing spectacles, whether the person has a long nose etc. Thus the semantic tagging of the images in the database is all done in the enrollment phase. The Retrieval sub-system accepts the verbal descriptions of a person’s face given by the user (or by running the semantic tagging on another face image) and retrieves images from the database by matching the descriptions given in the query probabilistically with the semantic description entries of the faces in the database.

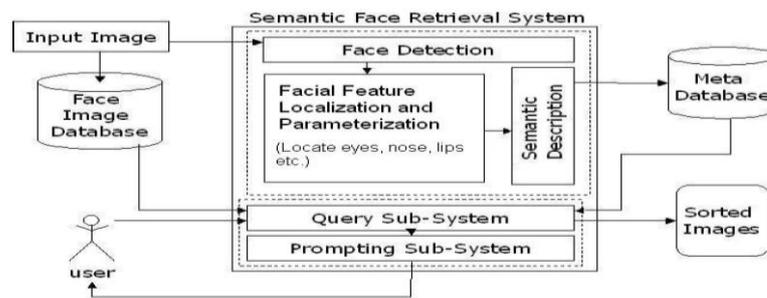


Fig5: Proposed SCNN Architecture for Face Recognition

IV. RESULT AND ANALYSIS

The first experiment used for retrieving face images from database and then for training the machine using Principal Component Analysis Algorithm for test. The results of these experimental runs are presented in following figures. In Figure7 the after training the machine and detecting the face the RGB image is converted into Gray Scale image for more efficiency. The same diagram also show some feature extracted as eyes, lips, nose. By training by using SCNN with PCA Algorithm the time required to train the machine is less. PCA is dimensionality reduction method and retain the majority of the variations present in the data set. It capture the variations the dataset and use this information to encode the face images. It computes the feature vectors for different face points and forms a column matrix of these vectors. After calculating the feature vector it calculate the mean of the face then it will normalize the each input face image by subtracting from the mean face then computing the covariance matrix for it, and calculate the eigen-values of the covariance matrix and keep only the largest eigen-values, then computing the eigenvector for covariance matrix using that matrix eigen-face are computed contacting highest information of the face image according to that it will compute the projected image.

The efficiency and performance level is better with compared to NN and CNN. As SCNN stores semantic information in the database the machine after feature extraction takes less time to match it with the data fed in the database. Semantic information includes eyes shapes, lips length, hair color, forehead width and nose length.

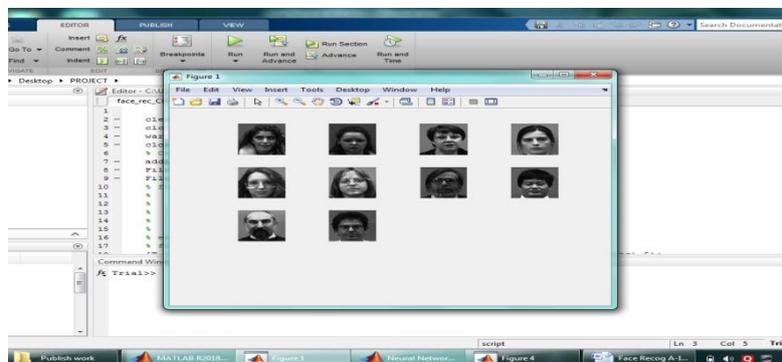


Fig 6: Face Retrieval from Database

The implementation results is shown in this Figures (Refer Fig 6 & Fig 7)

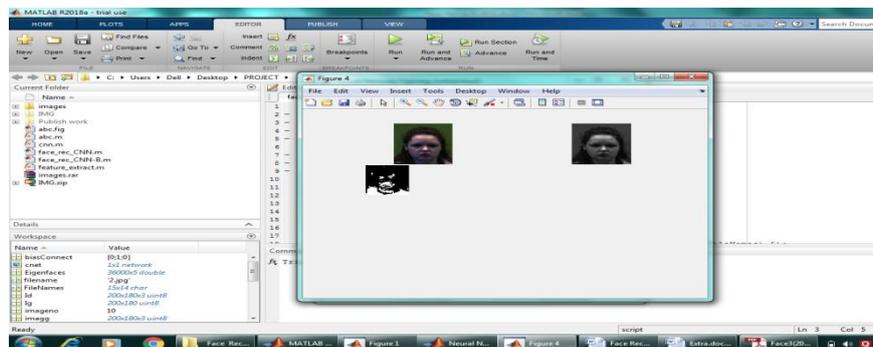


Fig7 Result of Converting RGB image into Gray Scale image and Feature Extraction

The performance Analysis is shown in the below table (Refer Table1)

Table1: Comparative Chart of 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

V. CONCLUSION

This paper has presented automated periocular recognition using CNN with outperforming results and significantly smaller complexity. In particular, we proposed a robust and more accurate framework for the periocular 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. 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. It will be our future work to investigate improved architecture which enables joint learning of semantic information explicitly as well as preserving the network integrity.

REFERENCES

Journal Papers:

- [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"

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