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Face Recognition using Deep Neural Network Across Variationsin Pose and Illumination

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Abstract--- Face recognition is an active area of research in computer vision. It is one of the fastest growing biometric systems over the past years. Several research efforts have been carried out to recognize the face images using different techniques ranging from appearance-basedmethod, feature based method and hybrid method with different results. However, face recognition is a challenging task due to the facial expressions, occlusions, variations in pose and illumination variation etc. To handle the pose and illumination variation in face images, this paper developed an architecture for face recognition using deep neural network. Convolutional neural network is trained to recognize the face images. The developed method is tested on ORL database by varying feature maps to find the best architecture. Results showed that the proposed method with architecture 15-90-150 provide better results compared to the state of art methods. It is also proved that the proposed model is robust to pose and illumination variation.

Keywords--- Biometric Authentication, Convolutional Neural Network, Face Recognition.

I. INTRODUCTION

Authentication is the process of recognizing the identity of a person or user. Authentication system can be divided into two major groups. (i) Non-biometric based authentication and (ii) Biometric based authentication. Non-biometric based authentication checks for an identity that a person carries some objects such as key and card. Non-biometric authentication system is further classified into knowledge-based authentication and object-based authentication [1]. Password, keys, PINs and token are the example of non-biometric based authentication which can be stolen, misplaced, forgotten and guessed by an attacker. To alleviate the limitations of non-biometric based authentication system, biometric based authentication system has been introduced.

Biometric authentication is the technique of identifying a person based on his/her behavioral or physiological traits such as palm print, fingerprint, vein pattern, retina, face, iris, voice, signature and finger knuckles. Using biometric traits for a person or user authentication is becoming convenient, robust and significantly more accurate than non-biometric based authentication. This is because biometric traits cannot be stolen or forgotten, very difficult to copy and manipulate [2]. Each biometric trait has their ownfeatures.

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Face recognition has gained more attention from the researchers and online service providers over the past decades. Face recognition is defined as the process of automatically identifying a person from the features of face including nose, eyes, mouth and skin color [3]. There are many techniques have been developed for face recognition.Face recognition has many applications in many fields like information security, surveillance systems, entertainment, employee control, social network applications and mobile applications.However, biometric authentication based on face features remains a highly challenging task since none of the method provide robust solution to all situations like pose invariant, facial expression, illumination variation [4]. Therefore, it is essential to develop an automated method for face recognition in order to solve the issues of existing methods.

Neural networks have been successfully applied for solving complex problems. Recently, deep neural networks have been explored for pattern recognition and image analysis. In this work, we propose a deep neural network for face recognition. Convolutional Neural Network (CNN) is chosen. The CNN architecture is designed for handling various situations like variation of poses and illumination variation. CNN consists of many layers. Proposed model used three main layers such as convolution layer, subsampling layer and fully connected layer. Each layertakes a multi-dimensional arrayof numbers as input and produces another multidimensional array of numbers as output, which thenbecomes the input of the next layer.Proposed method is tested on ORL face database to prove its efficiency.

The outline of this paper is structured as follows: Section 2 discusses the review of related work in this domain. Section 3 explains the functioning of the proposed face recognition scheme. The obtained simulation results and comparison are presented in Section 4. Finally, Section 5 conclude the paper and suggests the future enhancement followed by relevant references.

II. LITERATURE SURVEY

There exists enormous literature which concentrate on face recognition. In the following section, the paper focuses on the review of the previous articles regarding face recognition.

A Comparative study of various face recognition methods including Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA), Support Vector Machine (SVM), Wavelet

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Transform (WT), Artificial Neural Network (ANN) and hybrid method presented by Bhele and Mankar [5]. Kaushal and Raina [6] proposed a face detection method which is based on Gabor wavelet transform and ANN. Gabor filter-based feature vectors were extracted from the facial images. PCA adopted to reduce the dimension of the feature vector. Multilayer Perception (MLP) performed the classification task. Another interesting article based on Gabor wavelet and ANN reported in [7]. Wavelet features were extracted from the input images and then used as inputs to the ANN. Two ANNs namely MLP and Radial Basis Function (RBF) employed for classification. Proposed method validated on ORL database. Better results obtained using MLP. A combined method using wavelet transform and ANN presented in [8]. Facial features were extracted using Gabor wavelet transform. Back Propagation (BP) network employed to classify the images. Proposed method tested on AT & T and Yale face database under varies illumination conditions. An average accuracy of 93% obtained using BP network. Rawat [9] proposed a face recognition method using BP neural network. Proposed method begins with some preprocessing techniques like image resizing and normalization, and the normalized image is taken as feature vectors to be trained by BP neural network. This method failed to provide high recognition rate.

Syafeeza et al. [10] used 4-layer Convolutional Neural Network (CNN) for biometric authentication system. Proposed scheme can handle the facial images that contain pose, occlusions and illumination variation. Results showed an accuracy of 99.5% and 85.15% on AR and FERET respectively.

Khalajzadeh et al. [11] presented a hybrid system using CNN and Logistic Regression Classifier (LRC). Results showed improved recognition rate than other methods. Kamencay et al. [12] designed a face recognition system using CNN.

Performance of the method is compared with PCA, K-Nearest Neighbor (KNN) and Local Binary Pattern Histogram(LBPH). CNN outperforms the other methods. Blanger et al. [13] developed a face recognition library. CNN with 6 layers designed to perform classification. Proposed library achieved an accuracy of 98.14%.

III. PROPOSED METHODOLOGY

CNN is a kind of deep neural network were introduced to solve the problems of ordinary neural network like MLP. CNNs are feed forward networks offer the potential of extracting the most important details from the unprocessed (raw) input image.

It does not require any preprocessing. Additionally, CNNs have the capability of recognizing patterns with extreme variability and some geometric transformations such as scaling, rotation, translation and noise [11]. A CNN consists of one or more convolution layer, subsampling or pooling layer followed by one or more fully connected layers as depicted in Figure.1. Convolution layer performs the convolution operation on the image pixels within the kernel or receptive field and kernel weights.

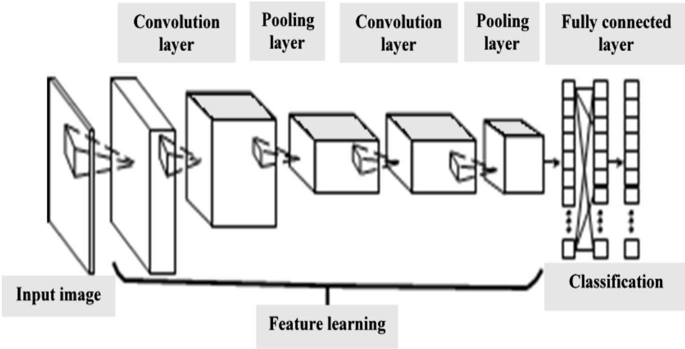

Figure 1: Architecture of CNN

The output of the convolution layer is the sum of the pixel values within the kernel multiplied by the corresponding kernel weight. It is used to detect the presence of the feature like edges, curves, nose ear, and mouth within the image.ANN attempt to learn a function by taking a combination of all of the functions at each stage in the network. Convolution is a linear operation, so combining many convolution layers will still only allow us to learn a linear function.

This unfortunately is not adequate for most real-world tasks.To tackle this problem, non-linear function is introduced.In CNN, this is done by applying a non-linear function to each of the feature maps produced in the convolution layers.

The most common non-linear function used is the Rectified Linear Unit (ReLU).

It is an element-wise operation which replaces negative values with 0.

It's one of the most widely used non-linear functions in neural networks because it has some nice properties which help to avoid problems such a gradient saturation during training.

Pooling layers are a form of downsampling which usually follow convolution layers in the neural network. Its function is to progressively reduce the spatial size of the representation to reduce the number of parameters and computation in the network. Pooling layer operates on each feature map independently.The most common approach used in pooling ismax pooling.Fully connected layer is the last layer of CNN. It allows the network to learn a function which maps the final layer of high-level feature maps to each of the image classifications.

CNN layers alternate between convolution layers with feature map$C^i_{x,y}$is defined as,

$$C^i_{x,y} = f(I^i_{x,y} \otimes W_{x,y} + B_{x,y}) \quad (1)$$

and pooling layers with feature map$P^i_{x,y}$ is expressed as,

$$P^i_{x,y} = f(I^i_{x,y} \otimes w_{x,y} + Gb_{x,y}) \quad (2)$$

Where,B and b-bias, W and w -Weight,f-activation function,G -matrix whose elements are all one and $\otimes$-convolution operator

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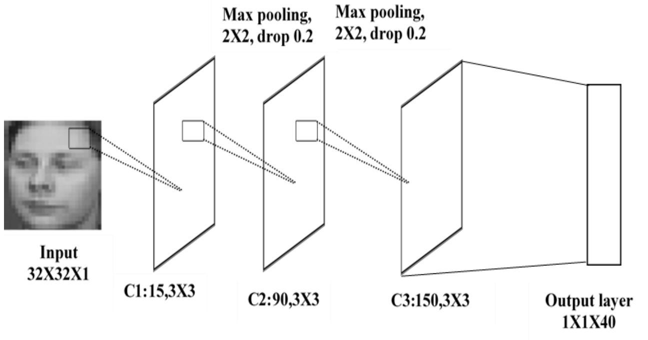

Figure 2: Structure of proposed CNN

Figure.2 shows the structure of proposed CNN. The proposed CNN has input layer, 3 convolutional layers, subsampling layer and fully connected layer. Size of input image is considered as 32 X32, So, ORL face images were resized to 32X32 to be compatible with proposed method. First convolution layer computes the output of neurons that are connected to local regions in the input, each computing a dot product between their weights and a small region they are connected to in the input volume. In this study, first convolution layer has 15 feature maps with 3x3 receptive fields. ReLUwas used to improve the sparse features of the CNN.

It applies an elementwise activation function, such as the max(0; x) thresholding at zero. Pooling or subsampling layer performs a down-sampling operation along the spatial dimensions resulting in volume. Subsampling layer has 8 features with a receptive field of 2x2. Output was dropped out with the probability 0.2. Max pooling method used. The second convolutional layer contains 90 feature maps with a receptive field of 3x3.

The second Subsampling layer has 16 features with kernel 2x2 and output was dropped out with probability 0.2. Third convolutional has 150 feature maps with a receptive field 3x3.

Fully connected layer computes the class scores, resulting in volume of size [1X 40], where each of the 40 numbers corresponds to a class score.The output of last layer was passed to the soft max. The final output was a classified distribution with respect to 40 subjects.

IV. SIMULATION RESULTS AND DISCUSSION

In this section, the experimental results of the proposed face recognition on public database are shown.

A. Research dataset

To evaluate the efficacy of the proposed face recognition system, several simulations are conducted on ORL face database [15]. Some sample images of ORL database are shown inFigure. 3.

The ORL database contains 400 face images of 40 individuals.

There are 10 images per person, one for each facial expression laugh, without laugh, open eyes, closed eyes, beard, beardless, with glass, without glass, sad and sleepy. All the images are gray scale image with 112x92 pixel array whose gray levels varied between 0 and 255. Image files are in PGM format.

Figure 3: Sample of ORL face images

Number of data and classes present in the ORL database are summarized in Table 1. Also presented the number of train and test image partitioning for ORL database.

Table 1: Summary of database

No. of images	No. of training images	No. of testing images	Classes	Train sample per subject	Test sample per subject
400	320	80	40	8	2

B.Preprocessing

Preprocessingphase for ORL face database requires image resizing. Figure.4. illustrates the image resizing phase for ORL database. Size of ORL database image is 112X92 is resized to the size of 32X32 with pixels 1024.

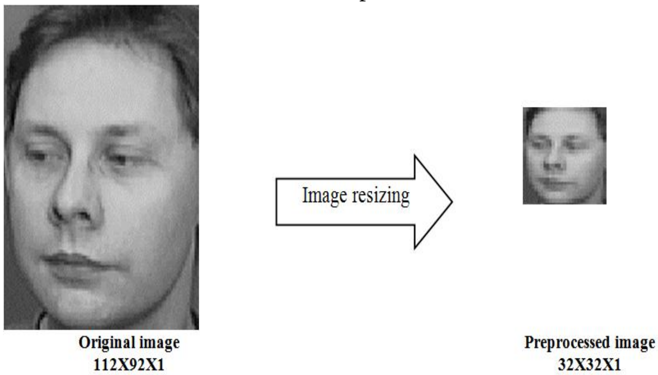

Figure 4: Image preprocessing

Resized image is passed to the convolution layer followed by the sub sampling layer. Each of the layers getsa 3D-input volume or feature map, and transformsit to another by means of convolutions and a nonlinearity.By stacking layers and downsampling theiroutputs, CNNs extract more complex and abstract featuremaps, which are, at the same time, invariant todistortions and translations. The last layer of CNN is fully connected layer. This layer computefinal descriptors of the input images, which canbe considered as global representations of images, orthey classify the input images into classes dependingon an objective function.

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C. Performance analysis

Proposed face recognition system is implemented and analyzed in MATLAB 2018 platform. The experiment is conducted to find the best model among different architectures:15-30-150, 15-45-150, 15-60-150 and 15-90-150. The number represents the number of feature maps at C1, C2 and C3 layer. Table 2 shows the performance for ORL database. The best accuracy of 98.75 is obtained with 15-90-150 architecture.

Table 2: Efficiency of the proposed architectures

Architecture	Accuracy (%)
15-30-150	93.75
15-45-150	94.5
15-60-150	96.25
15-75-150	97.5
15-90-150	98.75

Further to this, efficiency of the proposed method is compared with other existing methods found in the literature including Wavelet-BP [8],CNN[10],CNN-LRC[11],CNN[12] and CNN[13] in terms of mean accuracy.Table 3 compares performance of the proposed method with the other methods.It can be seen that the proposed method outperforms the other methods taken for analysis by providing high accuracy.Classification accuracy for various methods are graphically shown and compared in Figure.5.

Table 3: Comparison with other methods

Researchers	Method	Accuracy (%)
Xu et al.[8]	Wavelet-BP	93
Syafeeza et al. [10]	CNN	85.15
Khalajzadehet al.[11]	CNN-LRC	80
Kamencayet al.[12]	CNN	98.3
Blangeret al.[13]	CNN	98.14
Proposed method	Deep learning	99.25

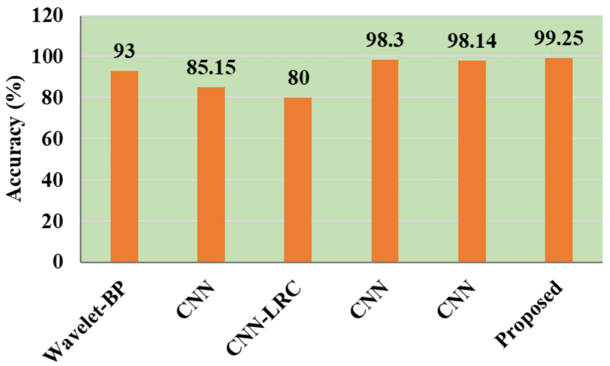

Figure 5: Comparison of accuracy for various face recognition methods

V. CONCLUSION AND FUTURE ENHANCEMENT

In this paper, a new method for face recognition using deep neural network is presented. A CNN is designed with three convolution layer and subsampling layer. First convolution layer, C1,detects the edges from the face image. Second convolution layer, C2, detects the simple shaped using edge features obtained in first layer. Higher level features are extracted at the third convolutionlayer. The overall efficiency is obtained using different architectures. Empirical findings proved that it is possible to achieve high recognition rate using CNN. For future enhancement, the proposed method will be extended to enhance the accuracy utilizing bio inspired computing algorithms.

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