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A Robust Face Recognition Model based on Convolutional Neural Networks

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Abstract

In computer vision and machine learning recognition of facial images is considered as one of the important research areas due to numerous problems in it, i.e. (i) expression problem: in which same individual shows number of expressions, (ii) illumination problem: in which face images of the same individual are taken in different varying light conditions and (iii) problem of poses: in which face images of the same individual are taken at various pose angles. Deep learning is a new area in machine learning research with the main objective of reducing the gap between artificial intelligence and machine learning. In the literature, deep learning architectures have proved effective in solving various classification problems. In this paper, we have proposed a robust deep learning model called deep convolutional neural network for solving the three challenging problems in face recognition i.e. expression, illumination and poses. Brief overview of deep learning and its various architectures are briefly explained. Convolutional neural networks are explained in detail. Experimental results of the proposed approach have been performed on six publically available face image datasets; the images in these six datasets have images with variation in illumination, poses and expression. Performance of the proposed approach is compared with other shallow architectures in literature and it is observed that the proposed approach performed well for all the three challenging problems in face recognition and is more efficient and robust as compared to other shallow architectures in literature.

Keywords: *Robustness, efficiency, deep learning, face recognition, principal component analysis, linear discriminant analysis, independent component analysis, Gabor wavelet transform, neural networks, convolutional neural networks*

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INTRODUCTION

Big data associated with the problem of face recognition can be projected into sub-spaces or clusters so that the given problem can be divided into sub-problems. Each sub-problem can then be optimized with an appropriate model [1]. One of the approaches of dividing a given problem into sub-problems involves projecting the big data to various sub-space grids, where each sub-space grid represents a sub-problem [2–5]. A given problem can also be divided into sub-problems by projecting the associated data to various clusters where each cluster represents a sub-problem [6–9]. Each sub-problem can then be represented independently with various models which can be combined by using a rule based system [10].

In machine learning and artificial intelligence, face recognition is considered to be one of the important research areas due to its numerous applications, i.e. access control, security purposes, investigations of database of images, verification of identity, surveillance, forensics etc. Non-inquisitive property of this system is considered as one of the important advantages i.e. it can work in passive manner. The factors which make face recognition a challenging task are: problem of illumination, i.e. multiple face images of the same individual are taken in varying lightning conditions; problem of poses, i.e. multiple face images of the same individual are taken in different poses at various angles; problem of expression i.e. face images of the same individual have different expressions like anger, smile, surprise etc.; problem of occlusion, i.e. when large part of the face image gets invisible [11]. Recognition of faces images are generally classified into the three main categories i.e. approaches based on holistic methods, local features extraction methods and hybrids methods. Approaches which are based on holistic methods extract the features from the whole facial image of the individual and those features are then used for recognition purpose, some of the holistic approaches are Gabor Wavelet Transform [12, 13], Independent Component Analysis (ICA) [14], Local Discriminant Analysis [15], and Principal Component Analysis (PCA) [16]. Approaches which are based on local feature extraction methods extract the features at selected points on the face image of the individual and those selected features are then used for recognition purpose. Finally, approaches which are based on hybrids methods use the property of holistic methods as well as local feature methods and the combined features are used for recognition purpose. In literature, various techniques of machine learning have shown good performance in various areas like various classification tasks [20, 21, 23, 25, 26], recognition [17–19, 22, 24, 27, 30], prediction [28] and decision making in robotics [29].

A new area of research in machine learning known as deep learning, also, second generation neural networks with the main objective is to reducing the gap between artificial intelligence and machine learning. From the past several years, deep learning algorithms have shown outstanding results in various classification tasks [31]. The models in deep learning i.e. deep neural networks have the characteristics to learn the underlying patterns automatically from the datasets containing large quantity of data like images etc. Deep learning models use number of hidden layers, normally, the number of hidden layers are more than two; such a combination helps the network in training process. There are number of architectures available in deep learning, some of them gained large popularity i.e. convolutional neural networks have performed well in various image classification problems. In convolutional neural networks, there are number of feed forward layers interlinked with each other, implementing convolution filters. These convolution filters are followed by pooling layers or we can say reduction layers. All the layers in this network originate a high level abstract feature which is similar as that of visual cortex in human beings which processes visual data as receptive fields [32]. The rest of the paper is organized as follows: literature review of various deep architectures for face recognition is given, deep learning is discussed briefly, and proposed approach of deep convolutional neural network is explained with experimental results on six benchmark face datasets, performance comparison of proposed approach with other shallow architectures and finally conclusion.

LITERATURE REVIEW

There are number of deep learning architectures proposed by various researchers in literature. Chan *et al.* proposed a deep learning based architecture for image classification [33]. It is based on number of processing units i.e. block wise histograms, binary hashing and the last unit is called cascaded PCA. For learning multistage filter banks, PCA has been used; block histograms and binary hashing have been used for pooling and indexing purposes. The authors called their network as PCANET. In this approach, two variations of PCANET were used; one is called LDANET and the other as RandNET. Both LDANET and RandNET share same topology as that of PCANET but differ only in cascaded filters which are either selected randomly or learned from LDA. The authors tested this network on number of datasets i.e. Extended Yale B, LFW AR, FERET, MNIST etc. for various tasks and the results obtained by the authors demonstrate the potential of this network for texture classification and recognition.

Hu *et al.* have proposed discriminative deep metric learning approach for verification of faces in the wild [34]. This approach is different as compared to existing metric learning based used for face verification task, which aims to learn a Mahalanobis distance metric to maximize the inter class variations and minimize the intra-class variations. In this approach, a deep neural network is trained which then learns a set of hierarchical non-linear transformations to project face pairs into the same feature subspace, in which the aloofness of each optimistic face pair is small than a lesser threshold and that of every negative pair is larger than a greater threshold correspondingly, so that the discriminative evidence can be subjugated in the deep network.

Krizhevsky *et al.* have proposed a deep learning approach for classification of images [35]. In this approach, a deep convolutional neural network was trained to classify the 1.2 million images of high resolution into 1000 different classes in the ImageNet LSVRC (2010) challenge. Good error rates were achieved on the test data set i.e. top1e: 37.5% and top5e: 17.0%. Deep neural network which was used in this approach has 60 million parameters and 650000 neurons and five convolutional layers, followed by max pooling and full connected layers. The final layer of this network is a soft-max (1000-way). For fast processing, efficient GPUs and non-saturating neurons were used in this approach. To overcome the overfitting problem, the authors used the dropout which showed good results.

Fan *et al.* have proposed a deep learning approach for face representation [36]. In this approach, deep network was used in a different way which is called pyramid convolutional neural network, which adopts a greedy filter and down sample operation. As a result of this, greedy filter and down sample operation, the computation is efficient and training is very fast. The design of the pyramid enables feature sharing through multiscale face depiction. After performing the experimental results on benchmark LFW dataset, accuracy of 85.8% was achieved with only eight dimension representation. Further, when this approach is extended to feature sharing pyramid, it obtains an accuracy rate of 97.3% on LFW benchmark dataset.

Nagpal *et al.* have proposed deep learning approach for face recognition [37]. In this approach, the authors used the perception that body weight deviations are an integral part of individuals aging process; nevertheless, the lack of connotation among the age and the weight of a person make it challenging to model these deviations for automatic face recognition. To overcome these problems, an approach was proposed by the authors using two dissimilar deep learning architectures i.e. sparse stacked de-noising auto-encoders and deep Boltzmann machines. In the loss function of these two architectures, the authors incorporated a body weight aware regularization parameter, which helps them to learn weight aware features. The authors performed the experimental results on WIT dataset and the results demonstrate the effectiveness of this approach.

Shah *et al.* have proposed an iterative deep learning approach for face recognition, which automatically learns discriminative representations from the images of the object and as well as from the raw face [38]. In the method, invariant features (low level translationally) are learnt by pooled convolutional layer, which is followed by artificial neural networks applied iteratively in a hierarchical fashion for learning of discriminate nonlinear feature exemplification of the input image-sets. The authors evaluated their proposed approach on various benchmark datasets for object recognition tasks i.e. CMU, YouTube celebrities, ETH-80 etc. and the results they got demonstrate the effectiveness of the approach.

To overcome the challenging problems of poses and illumination variations in face recognition, Zhu *et al.* have proposed a new learning based face representation called face identity preserving features (FIP); which is based on deep learning [39]. These features can considerably reduce intra identity discrepancies, while preserving discriminativeness between individualities. One of the important characteristics of these FIP features under any illumination and pose is that a face image can be reconstructed in the canonical view. This characteristic of these FIP features makes it possible to increase the performance of outdated descriptors, such as Gabor features and local binary patterns, which can be extracted from the reassembled images in the canonical view to eradicate discrepancies. To learn these FIP features, the authors designed a deep neural network which combines the feature extraction layer and the reconstruction layer. The feature layer encodes a face image into FIP features, while as the reconstruction layer transforms these FIP features to an image in the canonical view. The authors performed the experimental results on benchmark dataset i.e. Multi-PIE face database and the result which the authors got demonstrate the effectiveness of this approach as compared to other traditional approaches.

To overcome the various challenging problems like occlusions, poses, interpersonal discrepancies, low resolutions etc. Zhu *et al.* have proposed a deep learning approach that can recuperate the canonical view of face images, hence decreases the intra-personal discrepancies, while keeping the inter-personal discriminativeness [40]. The authors claimed that this approach directly learns the transformation from the face images of the individuals with a composite set of discrepancies to their canonical views. The authors performed the experimental results on the benchmark dataset i.e. LFW dataset and obtained good results as compared to start of art methods.

Huang *et al.* have proposed a deep learning approach for face recognition [41]. As in literature, there are number of face recognition systems which depend on feature demonstration specified by hand crafted image descriptor. The authors in this approach proposed a deep learning approach for obtaining supplementary balancing representations. In order to learn features from high resolution images, the authors used a convolutional deep belief network. Furthermore, to take benefit of global structure in an object class, the authors developed local convolutional restricted Boltzmann machines, that adventure the global structure by not pretentious immobile of features across the image, while keeping robustness and scalability to small misalignments. The authors also presented a new application of deep learning to descriptors other than intensity values of pixels, such as local binary patterns. The authors make the comparison of performances of networks trained with random filters with unsupervised learning and empirically exhibited that learning weights are not only important for acquiring good multilayer depictions, but also delivers sturdiness to the choice of the network architecture parameters. The results that the authors obtained after performing experiments demonstrate the effectiveness of this approach.

In order to handle the face verification in wild conditions, Sun *et al.* proposed a hybrid convolutional neural network-Restricted Boltzmann Machine (RBM) [42]. An important contribution of this work by the authors is that relational visual features are learned directly; after some processing of these relational visual features over number of layers, high level and global features are extracted. Further, in order to accomplish robustness, the authors construct multiple groups of convolutional neural networks. The authors performed the experimental results on Local Faces in Wild (LFW) dataset and the results demonstrate the effectiveness of this approach.

DEEP LEARNING

From the past several years, deep learning is a new area of research in machine learning with the main objective to reduce the gap between artificial intelligence and machine learning. Deep learning has its roots conventional neural networks available in the literature with the main difference of using multiple hidden layers which are normally greater than two and the training standards are also different as compared to traditional neural networks. In deep learning, numerous architectures are available and all the architectures are performing well; however, some of the deep architectures gained enormous property in which convolutional neural network is the one and has shown outstanding results especially in the field of the computer vision i.e. object recognition. In convolutional neural networks, number of feed forward layers is fully-connected with each other, implementing convolutional filters which are followed by other layers called pooling layers or reduction layers. There are other architectures in deep learning which have shown good results in the literature, such as restricted Boltzmann machines i.e. deep belief networks, stacked auto-encoders. Multiple hidden layer neural networks are called deep neural networks and those which have directed cycles are known as recurrent neural networks. In deep learning, as the datasets are huge and the network takes lot of time, hence GPUs are used to speed up the training process. It is important to mention here that deep learning comes after one of the initial neural network and biological stimulated algorithm used for binary classification known as perceptron, detailed description on perceptron is given by Freund and Schapir [43]. Our brain processes information over billions of neurons interlinked with each other and one of the most significant characteristic of the biological neurons is the capability to automatically fine-tune and to make new neural connections. Talking about perceptron, it has an input layer, this input layer has the direct connection with the output node; it emulates the biological process by using the weights and transfer function also known as activation function. In tradition neural networks, there was one input layer, one hidden layer and one output layer; for constructing of deep neural network multiple layers need to be added and the complex architecture gets designed as the hidden layers internment the non-linear relations. In the deep neural networks, the learning process is very slow, it is because once the errors are back-propagated from the last layer of the network to the first layer, they become very small (vanishing of the gradient) i.e. falling the learning process. To solve this problem, number of back-propagation variants is suggested but process of learning is still slow. In literature, new approaches have been used for training of deep neural networks i.e. supervised and unsupervised learning methods. Data should be labeled in case of supervised learning and in case of unsupervised learning, labeled data is needed; such type of learning is used in clustering, feature extraction etc. Various applications use the combination of supervised and unsupervised learning i.e. for extraction of features, unsupervised learning is used, then for classification purpose, supervised learning is used. For comprehensive detail of machine learning, one can refer to the work by Pedro [44].

ROBUST AND EFFICEINT DEEP CONVOLUTIONAL NEURAL NETWORK MODEL FOR FACE RECOGNITION

In this section, we will discuss about convolutional neural networks, their background, the proposed deep convolutional neural network model for face recognition and finally experimental results of the proposed on the six benchmark datasets having images varying in expression, illumination and poses.

Artificial Neural Network

Artificial neural networks (ANN) are sets of interconnected computational nodes and have the capacity in solving many computer vision problems. Nodes in ANN are called neurons structured in layers and have multiple interlinked connections between them. Layers in ANN are classified into three main categories i.e. input layer which receives the data that the network receives hidden layer or invisible layer which processes the input data and output layer which gives the final output. It is important to mention here that each neuron in the output layer and hidden layer have the connections to all the neurons from the previous layers in the network. Each edge in the network has a weight associated with it which indicates how strongly related the two neurons are with each other. ANNs are generally used for classification problems. Figure 1 shows the basic structure of an ANN.

Training of ANN

Artificial neural networks are trained with the data, there are various learning algorithms available in literature like gradient descent along with back-propagation can be used. In the starting step, weights are initialized in the network. The weights can be initialized by multiple strategies i.e. probability distribution or setting them randomly, after that three phases are repeated number of times. In phase first, input is propagated through the network and output values are calculated. In phase second, these output values are evaluated by using a loss function which determines how far off the present output is with the correct one. In the last phase, weights are updated so as to minimize the obtained error, this is done by finding the gradient of each neuron in the network. Reputation of all these three phases for all input instances forms an epoch. In order to find optimal solution for a given problem; there can be multiple epochs in an algorithm.

PROPOSED CONVOLUTIONAL NEURAL NETWORK MODEL

Convolutional neural networks are a distinctive type feed-forward neural networks which contain multiple convolutional layers. In CNN, convolutional layer comprises of learnable filters; these filters respond to assured features when convolved with a two dimensional (2D) input image and the output

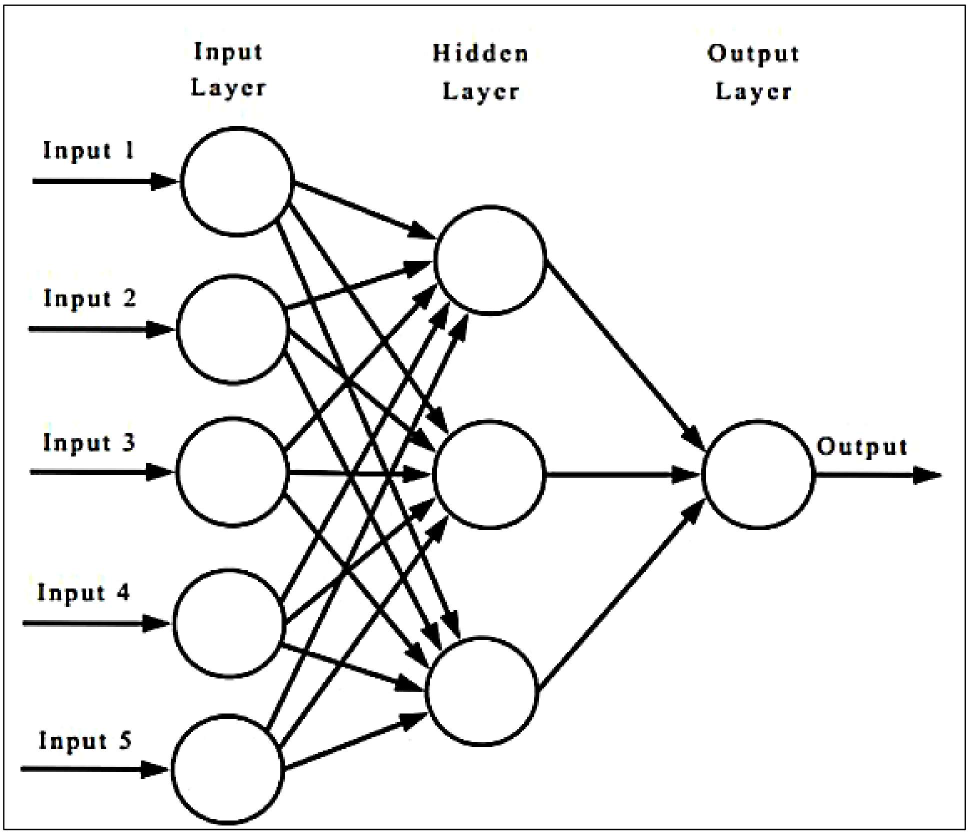

Fig. 1: *Basic Structure of an Artificial Neural Network Consisting of Three Types of Layers i.e. Input Layer, Hidden Layer and Finally Output Layer.*

is a filtered 2D output. In the CNN network, the first convolutional layer is applied to the input image, whereas the following layers take the output of the receptive proceeding layers. Figure 3 shows the basic structure of a convolutional neural network. As shown in Figure 3, CNN architecture is based on three concepts i.e. shared weights, local receptive fields and subsampling or polling. Deep convolutional neural networks are an active research area and are currently used in computer vision for various image classification tasks. While building a deep CNN architecture, selection of number of layers for the network is very important. The proposed framework for the deep CNN for face recognition is composed of five convolution layers which are alternated with ReLU layers, subsampling or pooling layers and dropout layers. There are two fully connected layers and a soft-max layer.

Convolution Layer

In this layer, each of the neuron the network connects a local of the input, and neurons in the equivalent feature map share the weights, that functions comparable a convolution by way of a filter. The equation of a convolution layer as given by Wenzheng *et al.*, is as follows [45]:

$$U_{n,m} = f * x = \sum_{i=1}^{H}\sum_{j=1}^{W} f_{i,j} x_i + m, j + n + b \quad (1)$$

$$where$$
$$f \in R^{H\times W} \text{ is the weight matrix of filters, } x \text{ is the input maps and } b \text{ is bias}$$

Pooling Layer

In order to reduce the computational training in convolutional neural network, pooling layer is used. In the literature, researchers use two types of pooling strategies i.e. max pooling and average pooling. Pooling layers are a technique to gain an invariant feature by aggregating low level feature over a small neighbourhood. Eqs. (2) and (3) show how max pooling and average pooling is calculated respectively:

$$M\_Pooling = \max_{i\in[1,k], j\in[1,k]} x_i + (m-1)\times d, j + (n-1)\times d \quad (2)$$

$$A\_Pooling: V_{m,n} = \frac{1}{k^2}\sum_{i=1}^{k}\sum_{j=1}^{k} x_i + (m-1)d, j + n - 1) \times d \quad (3)$$

ReLU Layer

The rectified linear unit is an activation function which calculates the function f(x)=max(0, x), where x denotes the input to a neuron.

Dropout Layer

In deep learning, the networks designed for solving a particular problem contain number of non-linear hidden layers, as a result of which the structure has complicated relationships between the inputs and the outputs. When the training data is less, nevertheless, several of these complex relationships will be result of sampling noise, so they will exist in the training set but not in real test data even if it is drawn from the same distribution. This leads to overfitting and there are number of methods proposed by various researchers for solving this problem of overfitting. Dropout is methods the helps to prevent the problem of overfitting. It refers to dropping out units (visible and hidden) i.e. temporarily removing the units from the network, along with its entire in and out connections [46].

Fully Connected Layer

This layer converts feature maps into a vector. It takes output from the convolution layer or ReLU or pooling layer and outputs an n dimensional vector, where n represents the number of classes.

Softmax

Softmax function is used for classification of multiple classes and it is the last layer in the convolutional neural network model for requiring the probability distribution of the classification. Eq. (4) shows how Softmax is calculated:

$$Softmax: f(x_i) = \frac{e^{x_i}}{\sum_{k=1}^{K} e^{k}} \quad (4)$$

EXPERIMENTAL RESULTS

We performed the experimental results of the proposed convolutional neural network model on six benchmark face datasets which are publicly available. These datasets contain face images with varying expression, illumination and poses. The seven face datasets that we used for experimental purpose are as follows:

1. Olivetti Research Ltd. Face dataset (ORL): This dataset contains 400 different images of 40 different individuals with 10 images of each person.
2. Faces94 dataset: This dataset contains a total of 3040 images of 153 individuals.
3. Yale faces dataset: This dataset contains a total of 165 images of total of 15 different individuals.
4. Yale faces dataset B: This dataset contains a total of 576 images of total of 38 different individuals.
5. FERET face dataset: This dataset contains a total of 11338 images of total of 994 different individuals.
6. CVL face dataset: This dataset contains a total of 797 images of total of 114 different individuals.

The first two datasets i.e. ORL and Faces94 have the face images varying in expression, the third and fourth datasets i.e. Yale and Yale B have the face images varying in illumination and the fifth and sixth datasets i.e. FERET and CVL have the face images varying in poses. The experimental results of the proposed convolutional neural network model on these six benchmark face datasets are given in Table 1 and performance comparison of the proposed approached with other shallow architectures is given in Table 2.

Table 1: *Experimental Results of the Proposed Approach on Six Datasets.*

S. No.	Dataset	# Images		Acc. in %age
		Training Set	Test Set	
1.	ORL	200	200	98.00%
2.	FACES94	1520	1520	99.21%
3.	YALE	90	75	97.33%
4.	YALEB	190	190	89.47%
5.	CVL	456	342	94.44%
6.	FERET	100	100	90.00%

As shown in Table 1, the proposed deep convolutional neural network performs well for all the three challenging problems in face recognition i.e. expression, illumination and poses. Table 2 shows the performance comparison of the proposed approaches with other shallow architectures in literature i.e. Principal Component Analysis, Linear Discriminant Analysis, Independent Component Analysis, and Gabor Wavelet Transform on the six publicly available face datasets: ORL, Faces94, simple Yale and YaleB, CVL and finally FERET face dataset. As given in Table 1, the proposed approach shows best result for the expression problem, after that for the illumination problem and finally pose problem. The proposed approach of deep convolutional neural networks is more robust as it can work on huge dataset and the experimental results show its efficiency. Figure 2 shows the performance comparison of the proposed deep convolutional neural network (DCNN) in graphical view with other shallow architectures in literature. As clearly shown in Figure 2, the proposed approach outperforms in the all the three problems as compared to other methods.

Table 2: *Performance Comparison of the Proposed Approach with Other Approaches for Images Varying in Expression, Illumination and Poses.*

S. No.	Method	Recognition Accuracy in %age for Three Problems		
		Expression	**Illumination**	**Poses**
1.	PCA	85.50 [17]	82.22[17]	68.00[17]
2.	LDA	88.50 [17]	86.66[17]	60.00[17]
3.	DCT	91.50[17]	76.66[17]	67.00[17]
4.	ICA	87.50[17]	71.11[17]	60.00[17]
5.	GWT	69.50[19]	88.80[19]	44.00[19]
6.	**Proposed approach**	**98.60**	**97.33**	**92.22**

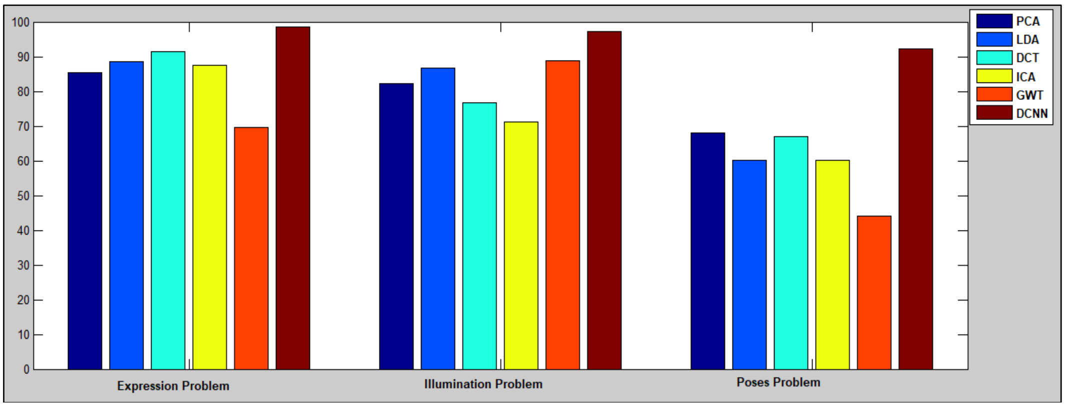

Fig. 2: *Performance Comparison of the Proposed Deep Convolutional Neural Network (DCNN) in Graphical View with Other Shallow Architectures.*

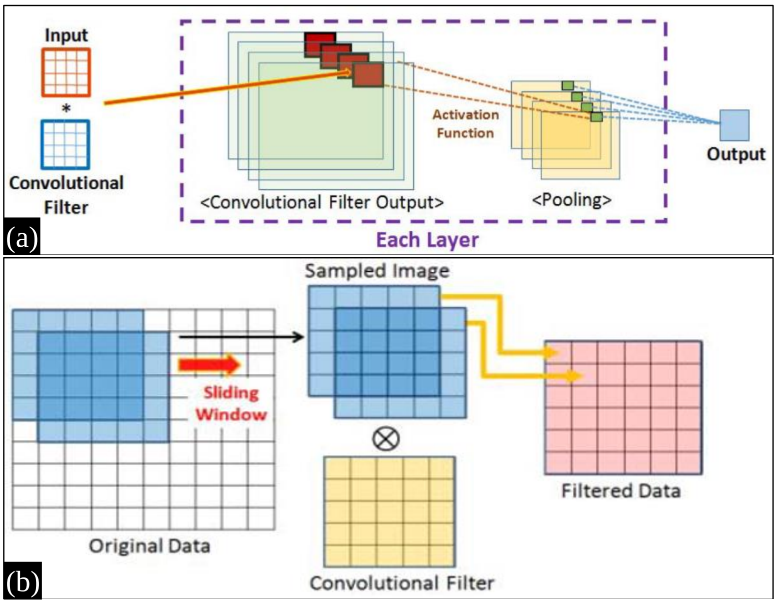

Fig. 3: (a) *Operation of a Convolution Layer and Polling Layer;* ***(b)*** *Operation of Convolutional Filter.*

CONCLUSION

In this paper, we have proposed an efficient and robust deep convolutional neural network model for three challenging face recognition problems i.e. expression, illumination, and poses. Literature review of various deep architectures for face recognition was also given. Experimental results on six publically available face datasets i.e. ORL, Faces94, Yale, Yale-B, FERET, and CVL Faces, varying in expression, illumination, and poses were also given. Performance comparison of the proposed DCNN with other methods for face recognition i.e. PCA, LDA, DCT, ICA and GWT was also given. It was observed that the proposed deep convolutional neural network model performs well for all the three challenging problems of face recognition problems i.e. expression, illumination and poses and is more robust as well as efficient as compared to other shallow methods for face recognition in literature.

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