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# Face Authentication Using Efficient Deep Convolutional Neural Network

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**ABSTRACT:** Recently face recognition, face verification becomes an interest scope of many researchers because they have been widely used in variety of real world applications. This work presents different strategies of constructing robust systems for face verification. An efficient deep Convolutional Neural network (CNN) is proposed to be used for face authentication. Although various methods are used to accomplish face verification, in this work, CNN is used instead because it has several merits over existing approaches. Exploring more robust CNN structures that can highly influence model accuracy is demonstrated in this work also. Although face authentication has received vast interest recently, there are very few works achieved using deep convolutional neural network. Thus, in this work, a robust model and efficient deep learning model is proposed to significantly enhance classification performance over existing works. The proposed models are evaluated using Labeled Faces in the Wild (LWF) dataset

**KEYWORDS**: Face recognition; convolutional neural network; Siamese Network; LFW; efficient deep learning

## I. INTRODUCTION

Recently, face recognition significantly becomes a vital research scope and there are several extensive works devoted to leverage and advance face recognition techniques [1, 2, 3, 4]. Also recent works from Google [5] and from Facebook [6] were presented. Valuable interest for this problem gains from wide range of problems needed to be manipulated. In addition, there is large number of real world applications using face recognition. One of the more valuable uses of face recognition is security applications whether using face recognition or identification. Face recognition can occur in one of two categories either face recognition or face authentication which is also called face identification. It is worth mentioning that face identification is comparison one to one. Means, given two images, the systems needs to tell whether the two images are identical or not whereas a face recognition is comparison one to all. Means, given an identity, the system needs to tell whether the input the identity is available within the dataset or not. In this work, both face authentication and recognition are presented.

Convolutional Neural Network (CNN) has been widely used in variety of applications. It achieves state-of-the-art for many challenge benchmarks. One of the most challenges that CNN achieves state-of-the-art is the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [7]. In addition, it is used for image recognition [8, 9, 10, 11], object detection [12, 13], image segmentation [14], and many other tasks.

In this work, CNN is used for challenge tasks represented by face recognition. The task is challenge and extensive research has been conducted to both tasks as it will be shown later. A robust CNN is proposed in this work to enhance existing state-of-the-art result. We propose novel CNN architecture for face authentications. Extensive experiments are conducted to evaluate proposed methods to show the robustness of our proposed approach. The work is compared to the most contemporary work and we show that we achieve superior results comparing to most recent works.

## II. RELATED WORK

Face recognition is not new tasks. There are huge number of works conducted to enhance and leverage benchmark accuracy. In addition, different methods are used for this task. Prior work can occur in one of two parts either using deep learning or without deep learning which uses handcrafted image descriptors such as using SIFT, LBP, and HOG as described in [2, 3, 4]. However, recently deep CNN becomes a dominant approach for wide range of tasks. It used widely in face recognition as demonstrated in [5,6, 15].

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## III. SIAMESE NETWORK

In this work, the same principle working of Siamese network for the face identification problem is recruited. However, different CNN architecture is used. To this end and before starting with the new architecture, it is worth to demonstrate how Siamese network works. It is originally used for signature verification but then it was adapted for face identification or verification. Siamese network is designed to receive pair of input face images and verify whether belong to the same person or not. Verifying identity is accomplished by non-linear similarity matric which is train by given pairs of positives and negative images to the Siamese network. Images belong to the same identity have small distance whereas images belong to different identity have large distance. Fig. 1 depicts the general sketch of Siamese network.

Thus, more robust CNN architectures used for face verification are explored in this work. By considering $X_1$ and $X_2$ are the first and second images respectively, CNN architecture is trained to reduce the distance between the two images when the two images belong to the same identity and enlarge the distance if they are not belong to the same person. It is also worth mentioning that the two CNN appearing in fig. 1 are identical. Originally only one network is trained because they share weights parameters implicitly.

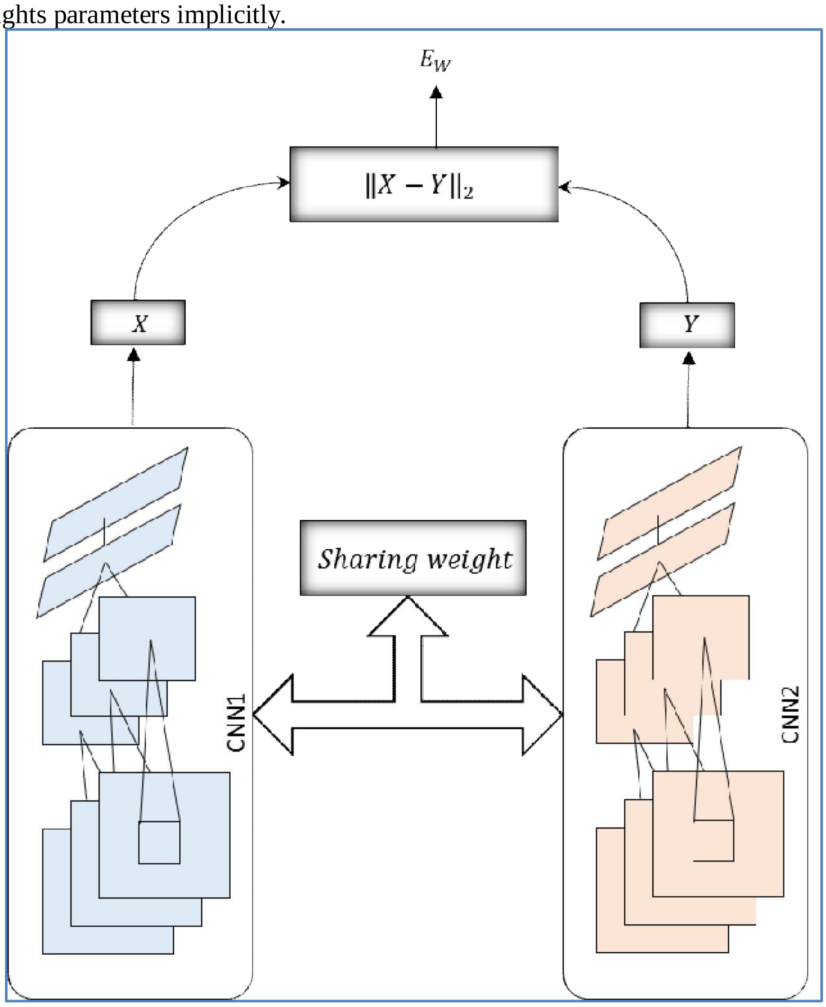


Fig. 3. General Structure of Siamese Network

The CNN used in this work receives pair of input face images with label referring whether the input images are the same or not. The general structure of CNN is shown in fig. 2. It is also important to refer to that contrastive loss

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function demonstrated in [16] is used in this work as loss function on the top of CNN structure. Contrastive loss function works by enforcing similar patterns close to each other and different patterns far from each other [16].

## IV. CONTRIBUTIONS

Robust CNN structures are used for face identification in this chapter. Face authentication is non-trivial tasks. Accordingly, more robust models used for face verification are extensively explored. Furthermore, new proposed model is presented at the end of this work. In addition, the proposed model is trained from scratch and also trained using pre-models. The last are the models implemented for gender classification used in this chapter. Thus we also provide study of whether training systems with the pre-trained models can influence system performance or not. The final proposed model achieves solid competitive results to the current state-of-the-art. Accomplished results are compared to the most recent contemporary works presented by deep CNN. Proposed model is evaluated on challenge Labeled Faces in the Wild (LFW) dataset.

## V. PIPELINE STEPS OF DESIGNING VERIFICATION MODEL

There are different methods used for implementing face verification problem using deep CNN. However, in this work, we use the same principle of operation Siamese network but a new CNN architecture for face authentication is presented. The following procedures describe how face verification generally works:

- The general structure of face verification used in this work is described in fig. 2.
- Prepare input images as a pair of input face images. Each pair images are either similar or dissimilar. Means the input pair images either related to same identifiers or not.
- Crop the input images to fit to the input size of CNN. In this work, we choose input face to be 128x128 pixels.
- Advance the input pair images to the CNN structures. As shown in fig. 2, one of those images forwarded to the network A and the second one advanced to the network B.
- Forward images in both networks and update weights according to the image passing through it. It worth mentioning that both networks share the weights. Hence both the network will be updated according to the both images. It is noticeable from fig. 2 that there are connections between the two networks meaning that they share weights.
- ConstrastiveLoss is the last layer used to connect the two networks and it is a method proposed in [16]. This function attempts making two input patterns close to each other if they belong to the same identify and far from each other if they belong to different identities. Means, the distance between similar input patterns is small if they are belong to the same person. Whereas the distance is higher if the two input face images are not the same person.

In this work, the effort is dedicated to explore a solid deep model for face authentication by discovering more reliable model parameters that can influence model performance. Hence, robust CNN is incorporated to enhance face verification accuracy. Also in this work, vast work is devoted to explore influence of different parameters that can highly influence model performance. Superior results are achieved on challenge benchmarks.

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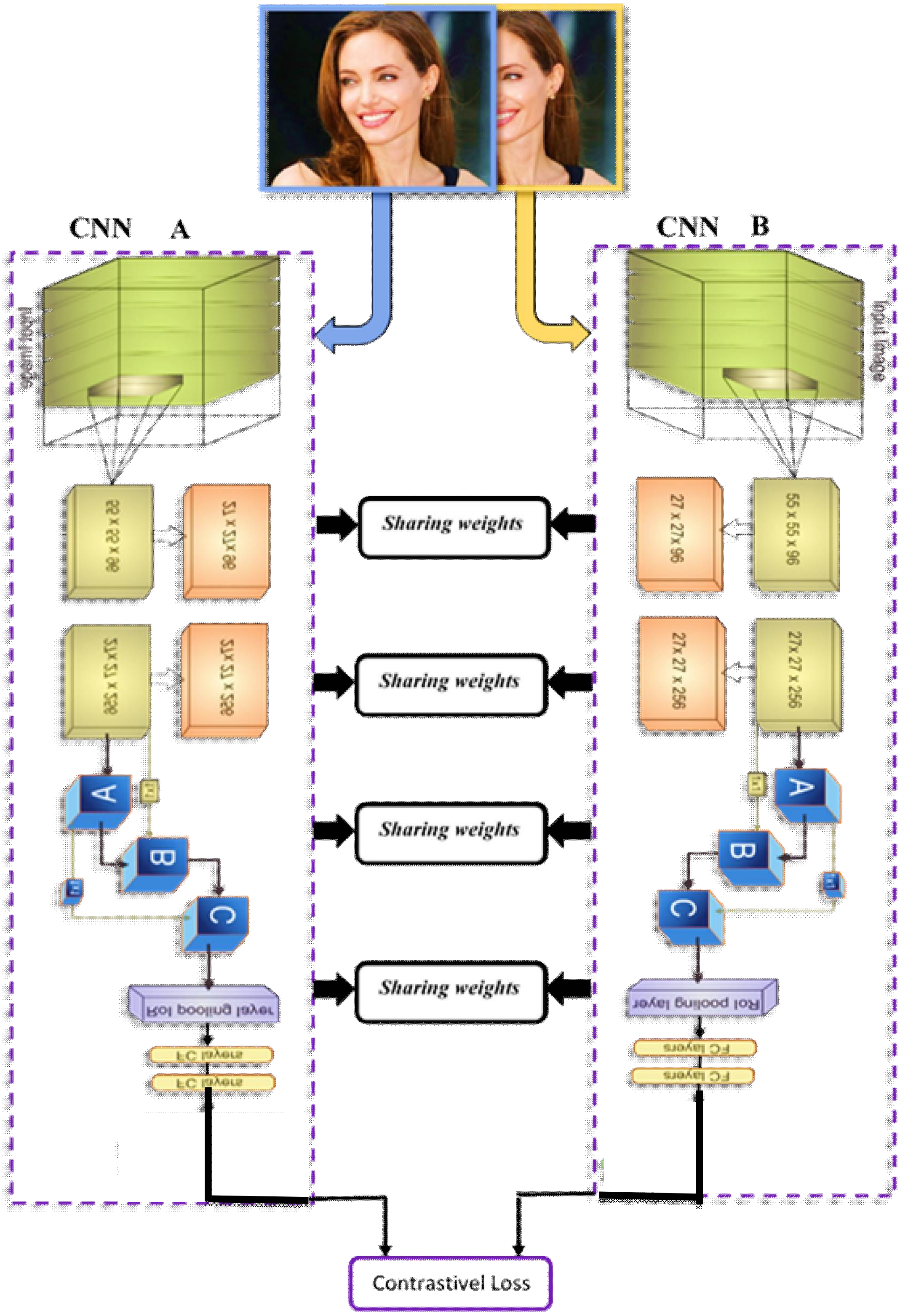


Fig.2. General structure of face verification model

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## VI. EXPERIMENTAL SETUP

To evaluate face verification model, challenge benchmark is used for evaluation. Labeled Face in the Wild (LFW) is used in this experiment. It is one of the most challenge dataset because it has different conditional environments. In addition, different poses and illuminations are also most common in this dataset. Sample of this dataset is shown in fig. 3. As demonstrated earlier, an efficient robust deep model is used in this experiment. It is worth mentioning that there are two settings for LFW either restricted orUnrestricted setting. In this study we used unrestricted setting. Superior accuracy is achieved in this work which is 98.3.

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Fig. 3. Sample of LFW dataset

## VII. CONCLUSION

In this work, face verification is presented. Different deep models are presented for the task is proposed. Specifically, Extensive experiments are conducted on challenge benchmark. We showed that different network architectures can lead to different model performance. Siamese network is used for face verification but a robust CNN is demonstrated. The presented CNN model is evaluated using challenge LFW dataset. Competitive results are achieved comparing with recent works. Superior results are achieved on Adience dataset comparing with all works accomplished on the same dataset

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