ISSN(Online) : *2456-8910*
International Journal of Innovative Research in Applied Sciences and Engineering (IJIRASE)
Volume 4, Issue 7, DOI:10.29027/IJIRASE.v4.i7.2021.823-827,January 2021

The enhanced security system for face recognition based on Deep network

Abha Upadhyay

Centre for Advanced Studies AKTU, Lucknow
Email: abhaupadhyay95@gmail.com

Abstract- Face recognition can have considerable significance to factual globe requisition (supplication) for instance video scrutiny, personage system evolvement, privacy & security system. A comparatively deep neural network provides better performance results in terms of accuracy & processing time. The introduced system based on a convolutional neural network (CNN) proposes enhanced building blocks by having normalization computation at the layers & it supplies speed-up to the system. The proposed CNN model utilizes to draw-out distinct features of face &ReLU used to classify faces into CNN fully connected layer. The experimental result showed that the proposed system achieved better performance result with enhanced face recognition security.

Keywords- Convolutional Neural Network (CNN), ReLU, Feature extraction.

I. INTRODUCTION

In today's society, the security of biometric images is one of the challenges. It can be one of the physical traits by which intelligent devices recognize a human being. Face recognition is the procedure of identifying the face of individuals by using a relevant system. Face recognition emerges as an improved personage identification technique because of its non-invasive behavior as compared to other biometric methods. In an unrestricted surrounding, face recognition can be effortlessly examined [16].

It can be surveyed that CNN is used as a recognition system. Conventional techniques based on the facile acquisition can lead to many issues such as pose estimation, occlusion, positioning, lighting, etc. These techniques only make use of some listed features of images [13]. And CNN based techniques make better extraction of complex features of faces. At the time of face recognition, distinct images of the human can be captured at different orientations and with a change in pose [12]. With the help of previously stored images captured picture being compared and result formulated. And it can ratify that this is relevant to a certain field of science, commerce, and administration.

Deep neural network classified into different approaches such as CNN (Convolutional neural network), RNN (Recurrent neural network), LSTM (Long short-term memory), encoder-decoder CNN, etc. [11]. And CNN can be largely used for images, whereas RNN and LSTM used for videos.CNN is one of the primarily used for face recognition systems as well as in other applications like handwriting recognition [7]-[10]. CNN is a type of artificial intelligence in which, after utilizing convolution algorithm, features can be extracted.

There are several pre-trained models of CNN such as Google Net, ResNet, VGGNet, etc. CNN input direct image and vigorous to the certain transformation such as location, scaling, rotation of pictures [9]. And CNN is also used as a classifier rather than a feature extractor. There are different classifiers such as SVM (Support Vector Machine), SoftMax, neural network, decision tree, etc. The main contribution of the proposed technique can be acquiring the impactful method with better performance. The proposed technique introduced improved CNN building blocks relatively with the layer Normalization process. And phase named as pre-processing, feature extractor and classification. In pre-processing, transparency and color transformation performed, followed by scaling and resizing. In feature extraction, using CNN, facial features are extracted. And in classification, the ReLU classifier is used for the classification of images.

Rest of the paper states about proposed methodology in section II, section III tells about experimental result and section IV states about conclusions.

II. PROPOSED METHODOLOGY

In applications such as recognition of pictures and categorization, CNN is demonstrated as most efficacious. CNN is a term of deep learning and is primarily used in identifying vision allusion [1]- [4]. CNN architecture is made up of different layers and contains a number of filters (also called Kernel or Neurons) that have weights that gets an update after every convolution [17]-[19]. Structured and conventional building blocks of CNN display in Fig.1. Layers of CNN are named as the Input layer, Convolutional layer, Poolinglayer, Fully connected layer, Softmax/Logistic layer and Output layer.

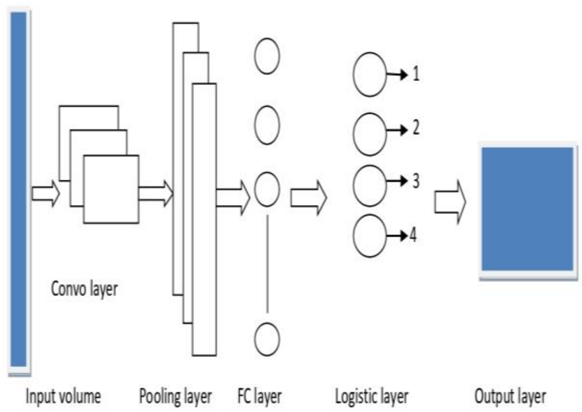

Fig. 1.Structured & Conventional building blocks of CNN

A. Input Layer:

This includes image data and image data denoted by the 3D array. And it has to be resized into a single column. Example: Before input, 28 x 28 images are transformed into 784 x 1.

B. Convolutional Layer:

In the CNN model, the Convo Layer plays an important role. The image function is extracted within this layer[15]. By reading image characteristics, convolution maintains the contiguous connection between elements by obtaining assistance from tiny pores of feeding images[21]-[25]. For the convolution method, Numbers of Filters is used and produces an activation map to be fed to the next layer of CNN as data.

C. Pooling Layer:

After convolution of feeding images, the pooling layer was used to lower down the contiguous volume. It can be used between the two layers of convolution [14]. It can be costly if you add a fully connected layer after two convolutional layers without applying average or max pooling. The pooling layer offers better outcomes for such conversions.

D. Fully Connected Layer:

There are kernels, weights & biases in the Fully Connected Layer. In general, one kernel layer is connected with the kernel of the next corresponding layer [6]. It is used to categorize images by practicing between certain forms. The ReLU or Softmax activation feature functionality can be referred to as the finishing pooling layer input (classifier).

E. Logistic Layer:

It is the final layer of the model of CNN that was put at the end of the layer that was completely connected.

F. Output Layer:

This is the output layer of CNN and it includes the tag that can be in the shape of single-hard encoded. The building block of the proposed CNN based face recognition schema can be represented in Fig. 2. And the technique is structured in three phases as given underneath:

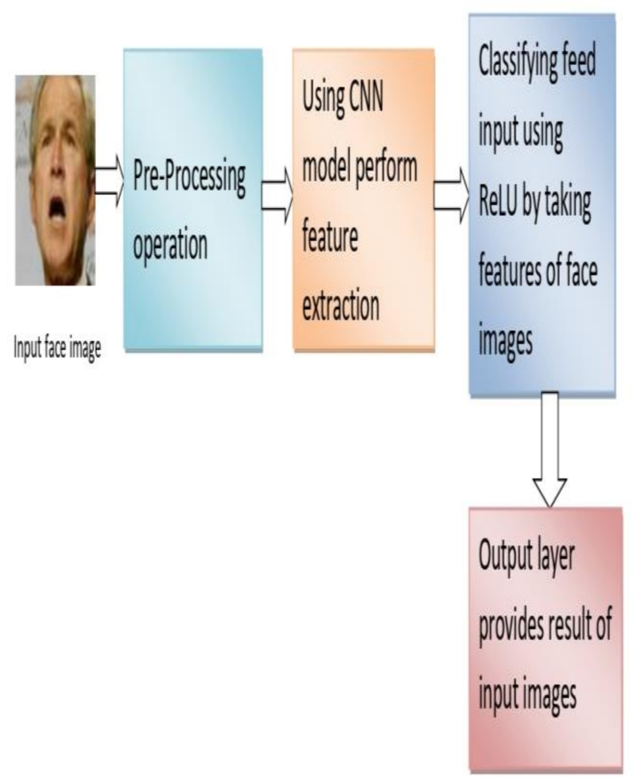

Fig. 1. Block diagram of the proposed technique

a) Input images gets resize at a suitable size.
b) For feature extraction, form a CNN block using ten layers named convolutional, max pooling, convolutional, max pooling, convolutional, avg pooling, convolutional, avg pooling convolutional and convolutional.
c) And then, after feature extraction, the ReLU classifier is used for classification.

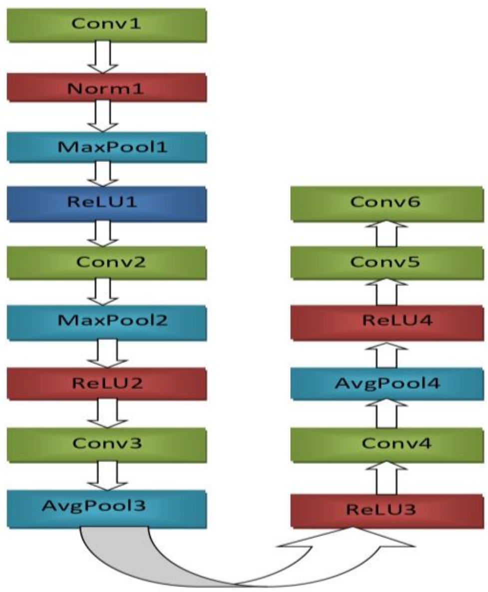

Fig. 2. Flow diagram of feature extraction using CNN

III. EXPERIMENTAL RESULT

The proposed system uses the LFW database to store more than 13,000 face pictures downloaded from online sources. And downloaded face pictures are of average size 190 x 185 pixels. And all target pictures are resized as 80 x 95 and Fig. 4 represents a list of face pictures used in the CNN model. And specification for the introduced technique can be discussed in Table 1.

Fig. 3. List of pictures used in CNN model

Table 1 The specification for introduced technique

Size of feeding picture	Error-1 leading rate epochs	Error-5 leading rate epochs	Rate of learning	Rate of Error-1	Rate of Error-5	Size
32x32x1	18	41	0.0010	95.9	98.0	20
32x32x3	26	25	0.0014	94.5	95.7	10
64x64x1	49	18	0.0010	91.0	98.5	30
64x64x3	35	33	0.0010	84.0	98.0	10
128x128 x1	22	45	0.0017	87.6	98.0	30
128x128 x3	31	15	0.0010	92.7	99.0	20

For training, 70% of pictures are allocated and the rest of 30% is allocated for testing. And the proposed system trained for 50 epochs and the effectiveness of the introduced system were examined based on error rate 1, error rate 2 and error rate 5. Error rate 1 identify according to identity in between target mark and leading class, error rate 2 finds when target mark can be leading three prognosis and error rate 5 finds when target mark can be the same to one of the lead five prognosis.

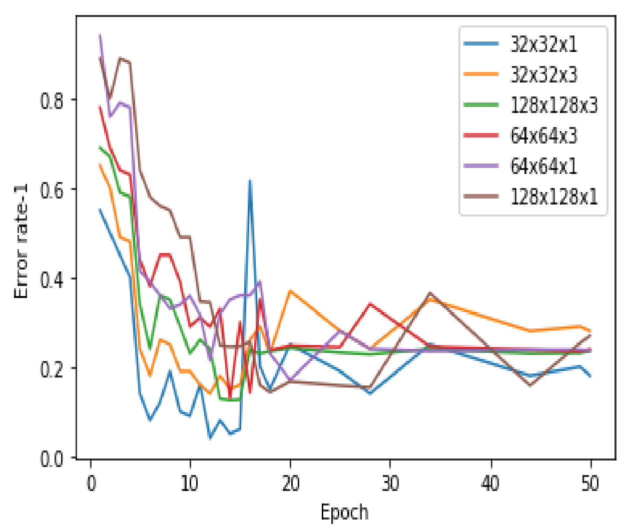

Fig. 4. Error rate-1 for introduced technique of CNN

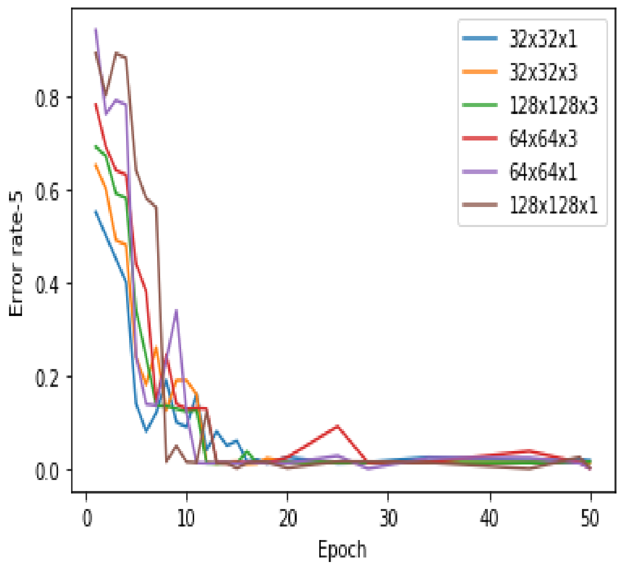

Fig. 5. Error rate-5 for the introduced technique of CNN

Fig. 5 presents Error rate-1 of the introduced model and Fig. 6 presents Error rate-5 of the introduced model. The proposed building blocks of the CNN model present their performance by showing Fig.5 and Fig.6. And output obtained by targeting images from the database.

IV. CONCLUSIONS

The proposed method introduced a heuristic estimation of the security system of face recognition using the CNN model. The distinguishing features of the presented technique can be that method utilizes the layer normalization at the initial layer regarding the training step and it provides a method to leads to a better performance rate. ReLU can be employed for the classification purpose of images.

REFERENCES

[1]. K. Delac, Recent Advances in Face Recognition, 2008.

[2]. P. Pinheiro and R. Collobert, "Recurrent convolutional neural networks for scene labeling," Proc, 31st International Conference, vol. 32, no. June, pp. 82-90, 2014.

[3]. Dan Ciresan, "Deep Neural Networks for Pattern Recognition."

[4]. Y. LeCun et al., "Backpropagation Applied to Handwritten Zip Code Recognition," Neural Comput, vol. 1, no. 4, pp.541-551, Dec. 1989.

[5]. A. S. Tolba, A, H. EL-baz, and A. A.El-Harby, "Face Recognition: A Literature Review," 2006.

[6]. S. G. Khele and V. H. Mankar, "A review paper on Face Recognition Techniques," 2012.

[7]. Michel Owayjan, Amer Dergham, Gerges Haber, Nidal Fakih, Ahmad Hamoush, Elie Abdo, "Face recognition security system," 2013.

[8]. Y. Bengio, "Learning Deep Architecture for AI," 2009.

[9]. M. O. Simon et. al., "Improved RGB-D-T based face Recognition," IET Biometric, vol. 5, no. 4, pp. 297-303, Dec. 2016.

[10]. E. Shelhamer, J. Long, and T.Darrell, "Fully Convolutional Network for Semantic Segmentation," IEEE trans. Pattern Analysis Mach. Intell, vol. 39, no. 4, pp. 640-651, 2017.

[11]. Xin Geng, Zhi-Hua Zhou, Kate Smith Miles, "Individuals Stable Space: An Approach to Face Recognition Under Uncontrolled Conditions," IEEE trans on Neural Networks, 2008.

[12]. Stan Z.. Li, Rufeng Chu, Shengcai Liao, Lun Zhang, "Illumination Invariant Face Recognition using Near-infrared images," 2007.

[13]. O. De Vel, S. Aeberhard, "Line-based face recognition under varying pose," 1999.

[14]. Changxing Ding, Chang Xu, Dacheng Tao, "Multi-Task Pose-Invariant Face Recognition," IEEE trans on Image Processing, 2015.

[15]. Musab Coskun, AysegulUcar, Ozal Yildirim, Yakup Demir, "Face Recognition based on Convolutional neural network," 2017.

[16]. Zhen Lei, Dong Yi, Stan Z. Li, "Learning Stacked Image Descrpitor for Face Recognition," IEEE trans on Circuits and Systems for Video Technology, 2016.

[17]. Gee-Sern, Jison Hsu, Yu-Lun Liu, Hsiao-Chia Peng, Po-Xun Wu, "RGB-D-Based Face Reconstruction and Recognition," IEEE trans on Information Forensics and Security, 2014.

[18]. Niall McLauhlin, Ji Ming, Danny Crookes, "Largest Matching Areas for Illumination and Occlusion Robust Face Recognition," IEEE transcations on Cybernetics, 2017.

[19]. Chuan-Xian Ren, Dao-Qing Dai, Hong Yan, "Coupled Kernel Embedding for Low-Resolution Face Image Recognition," IEEE Transcation on Image Processing, 2012.

[20]. Yin Zhang, Zhi-Hua Zhou, "Cost-Sensitive Face Recognition," IEEE transcation on Pattern Analysis and Machine Intelligence, 2010.

[21]. Shengchauan Zhang, Xinbo Gao, Nannan Wang, Jie Li, "Robust Face Sketch Style Synthesis," IEEE Transcations on Image Processing, 2016.

[22]. William Robson Schwartz, huimin Guo, Jonghyun Choi, Larry S. Davis, "Face Identification Using Large Feature Sets," IEEE Transactions on Image Processing, 2012.

[23]. Kwang Ho An, Myung Jin Chung, "Cognitive face analysis system for future interactive TV," IEEE Transactions on Consumer Electronics, 2009.

[24]. E.P. Vivek, N. Sudha, "Gray Hausdorff distance measure for comparing face images," IEEE Transactions on Information Forensics and Security, 2006.

[25]. Q. Chen, J. Yao, W.K. Cham, "3D model-based pose invariant face recognition from multiple views," IET Computer Vision, 2007.

[26]. Shu Zhang, Ran He, Zhenan, Sun, Tieniu Tan, "DeMeshNet: Blind Face Inpainting for Deep MeshFace Verification," IEEE Transaction on Information Forensics and Security, 2018.

[27]. Chunlei Peng, Xnbo gao, Nannan Wang, Jie Li, "Graphical Representation for Heterogeneous Face Recognition," IEEE Transaction on Pattern Analysis and Machine Intelligence, 2017.