INTERNATIONAL JOURNAL OF SCIENTIFIC PROGRESS AND RESEARCH (IJSPR) ISSN: 2349-4689
Issue 132, Volume 45, Number 04, March 2018

Secure Face Recognition using CNN

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Abstract*—Recognition technology isoneof the methods tofacilitate the modern gadgetsand securityequipments. Face recognition isadditionally utilizing for keeping dataof facial information of workersof anyorganization, residentsof any nation to deal with violations in unreasonableoccurrences. For making face recognition more dependableand quicker therearea few methodsare getting advanced each day. Quitepossibly the most robustand quick face recognitionsare based on CNN. This work planned dependent on the numerousconvolution module-based CNN system with standardization and straight redressed unit for normalizing and improvement of highlights with minibatch. The SoftMax classifier characterizes the faces in fullyconnected layer of CNN. For preparing ORL face dataset. Theaverageprecision accomplished is 98% for ORL Datasets. The trial resultsshowed that theproposed approach has improved the Face recognition execution with higher recognition precision.

***Keywords* - Face recognition,convolution neural network,SoftMaxfunction, batch normalization, deep learning.**

I. INTRODUCTION

After rapid advancement of artificial insight, Face recognition has indeed attracted attention becauseof its non-nosy natureand since it is main strategy for individual identification for human when it iscompared with different kindsof biometric methods. Face recognition can also beeasilychecked without thesubject individual's information in an uncontrolled climate.

As the historical backdropof Face recognition is reviewed, it isseen that it has been addressed in many research papers for example [1],[3]. Traditional strategies based on shallow learning have been facing challenges likeposture variation, facial camouflages, lighting of thescene, the intricacyof the image background, and changes in facial demeanor as in references [3],[4]. Shallow learning-based strategies just use from some basic featuresof imagesand rely upon artificial experience toextract sample features. Deep learning based techniquescan extract morecomplicated face features [5]–[8]. Deep learning is making crucial advances in tackling issues that haveconfined the best attemptsof theartificial knowledge local area for a long time. It has demonstrated to besuperb at revealing complex designs in high-dimensional dataand isalong these linesapplicable to bunchesof domainsof science, businessand government. It addresses the issueof learning hierarchical representations with asolitaryalgorithm or acoupleof algorithmsand has mainly beaten records in imagerecognition, natural languagepreparing, semanticsegmentation and manyother real world scenarios [9]–[11]. Thereare distinctive deep learning approaches likeConvolution Neural Network (CNN), Stacked Autoencoder [36], and Deep Belief Network (DBN) [12], [13]. CNN is for the most part utilized algorithm in imageand Face recognition. CNN isasort of artificial neural organizations that utilizesconvolution system toextract the features from the info data to increase the quantityof features. CNN was first and foremost proposed by LeCun and was initiallyapplied in handwriting recognition [14]. Hisorganization was the inception of asignificant part of the new architectures, and a genuine inspiration for many researchers in the field.

Therestof thiswork isorganized as follows. In segment 2, CNN architecture ispresented. In segment 3, theproposed algorithm isexamined. In area 4, the face database utilized in thispaper is introduced. Theexperimental outcomesare given in area 5. Finally, weexamineends in segment 6.

II. PROPOSED CNNSYSTEM MODEL

CNN is usuallyhaving maximal usage in the designing of computer vision related applicationse.g., imageprocessing. In various recognition application convolution operation used with filter toextract out the featuresof information image (here face). In other words,CNNsareacategoryof Neural Networks that have demonstrated powerful in areas, for example, imagerecognitionand classification. CNNsareasort of feed-forward neural organizations made upof many layers. CNNscompriseof channelsor bitsor neurons that have learnable loadsor parametersand biases. Each channel takesa few information sources, performsconvolution and optionally follows it with a non-linearity [16]. A typical CNN architecturecan be viewed as demonstrated in Fig. 2.1. Theconstruction of CNN containsdifferent mathematical operations likeconvolution, batch normalization, pooling, Rectified Linear Unit (ReLU), SoftMaxand fullyconnected.

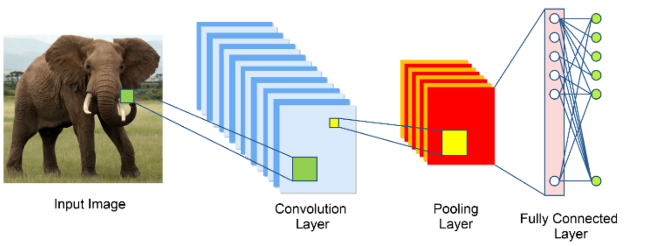

Fig. 2.1 A traditional Convolution Neural Networks design

A.ConvolutionOperation:

Theconvolution operation is basically used tocalculate thecorrelation between the kernel weightsand the imagepixels (or previous layer output). It isan element-wise multiplication operation followed byasummation between the kernel feature mapand the input, asshown in theequation below.

This isan important propertyof CNNsas it reduces the number of parameters. It isperformed asa matrix operation rather than an individual element-wise multiplication and summation in practice in almost all widely used deep learning libraries.

B.Batch Normalization Operation:

Batch normalization isa data normalization method that is help to improve theperformanceand speed of training process in deep learning systemse.g., CNN.

C. Pooling Operation:

Thepooling operation down samples the large image with replacing sub regions (e.g. 2x2 matrix) with asingle value. This valuecan beaverageof all theelementsof region or maximum value. Pooling layer decreases the dimensionalityof each activation map however keepson having the main information.

The information imagesarepartitioned intoa bunch of non-overlapping rectangles. Each area is down-sampled bya non-linear operation likeaverageor maximum. This layer achieves better generalization, faster intermingling, strong to translation and mutilation and is usuallyplaced between convolution layers.

D.ReLU Operation:

ReLU isa non-linear operation and incorporates units utilizing the rectifier. It isacomponent astuteoperation that means it isapplied per pixel and reconstitutesall negative values in the feature map by nothing.

E.Fully Connected Layer:

Fully Connected Layer (FCL) term alludes to that each channel in thepast layer isconnected toeach channel in the following layer. The goal of utilizing the FCL is to utilize these features for classifying the info image into variousclasses based on the training dataset. FCL is regarded as the final pooling layer taking careof the features toaclassifier that utilizes Softmax activation work.

F. Soft Max Operation:

Thesoftmax function isa function that turnsa vector of K real values intoa vector of K real values that sum to 1. The input valuescan bepositive, negative, zero, or greater than one, but thesoftmax transforms them into values between 0 and 1, so that theycan be interpreted as probabilities. If oneof the inputs issmall or negative, thesoftmax turns it intoasmall probability, and if an input is large, then it turns it intoa largeprobability, but it will always remain between 0 and 1.

III. PROPOSED METHODOLOGY

The main commitment of this research work is toobtain an efficient recognition algorithm with high accuracy. The general design of Face recognition procedure in this work is made upof threestages. It starts with pre-preparing stage: loading face dataset, shuffling and splitting of dataset for training and validation, proceeds with machine learning using extraction of facial features with *'sgdm'*optimization algorithm, and afterwardsextracted featureset isclassified for recognition accuracy testing of trained network. In our framework, Softmax Classifier is to realize final stage that isclassification on the basisof the facial featuresextracted from CNN.

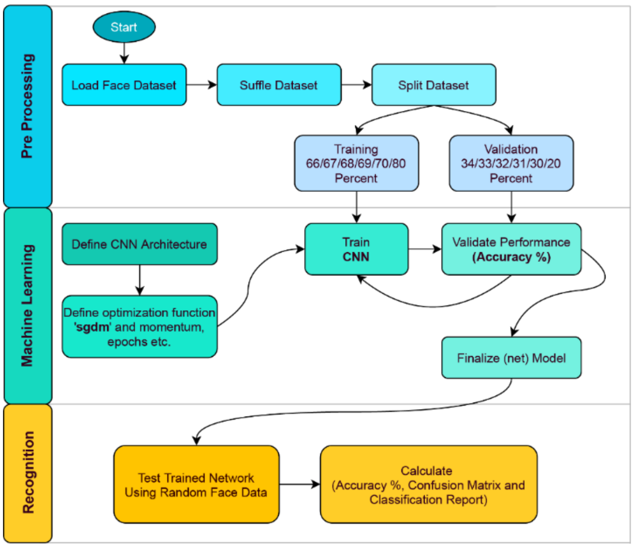

Figure 3.1 Stagesof proposed MM-CNN face recognition system

Stage 1: Pre-Processing

Thisstage is involving theoperation which covers thesteps to load the input dataset of faces (e.g. ORL). Load these datasets intosimulation environment for further operation followed byshuffling of facesamples. After that dataset ispartitioned into training and validation parts which is 66% to 80% used for training and 34% to 20% for validation respectively.

Stage 2: Machine Learning

The machine learning stageconstitutes the four parts, defining of CNN architecture, defining optimization function, training of network, validation of network asshown in Figure 3.1.Thisstage isextract featuresand train neural network using defined percentageof face dataset. The layered architectureof CNN isshown in figure3.3 for ORL Datasets respectively, with theentire detailed feature map, filter size (kernel) along with number of filtersof each convolution module.

Thereare 4 convolution modules for ORL face dataset. Every module has following layers:

A. 2D Convolution Layer

The face imagesare given as input to thisstageand 2D convolution isperformed with 3 × 3 filter (kernel) sizeon the image to get the 16 convoluted featuresor feature mapsof the input face image. Theoutput of this layer isshown in below Figure.Similarly, 32, 64, and 128convoluted features (feature maps) will beextracted from 2nd, 3rd,and 4thconvolution layers respectively.

Figure 3.2 ProposedMM-CNN Layer Graphused for ORL Dataset

B. Batch Normalization Layer

Batch normalization performs for normalization of data received from theconvolution layer i.e., feature maps. This layer refines the featuresasper batch size defined. Asa result, we'll get the different set of normalized features.

C. ReLU Layer

Rectified Linear Unit or ReLU layer is responsible for getting truncated featuresafter normalization and used for speed up the training processof deep learning.

D. Max Pooling Layer

In deep learning environment to reduce thesamplesizes (here face features) pooling layer is implemented. Here max pooling isperformed which means maximum valuesof sub regions isconsidered to down sample the features. Pooling layer isonlya bridge between twoconvolution modules. Thiscan't be used toconnect theoutput or fullyconnected layer.

Stage 3: Recognition

Previousstage has doneall the learning process from the given face dataset from ORL faces. After learning (extraction of face features) the neuronsare trained and classified intoclasses using another three layers. These layersare fullyconnected layer, soft max layer and classification layer. The working of layers isexplained below.

A. Fully Connected Layer

After getting output of final convolution module (hereoutput of relu_5 layer) will be reshaped intosinglecolumn and operate with the weight matrix and bias vector to get thespecified number of classes (here 28 person).

B. Softmax Layer

It is last activation function in the deep learning network which is used for multiclass logistic regression. In other words, used for network normalization to get theprobability distribution of network output. This helps topredict theclassof input or help toclassify the input.

C. Classification Layer

This layer shows the weighted classification i.e., after calculation of crossentropy loss gives the definiteclassof the input.

Here CNN is formed using different modules; theseare thecombination of convolution layer, batch normalization layer, relu layer and pooling layer. The input face information is travel from input layer toclassification through these modules.

For ORL face datasetkernel size is kept 3x3 and 8, 16, 32 and 64 feature mapsare generated in four modules.These modules designed with increasing order of feature maps. The increasing numbersof feature mapsare helpful toextract out the featuresout of featureextracted from previousstage. By thisapproach important featuresare filtered out. These refined featuresare then normalized using fullyconnected and SoftMax layer to get weighted probabilityof features ranges between 0 and 1.

Thisweighted vector is lead to decide the final class(person) of the face.

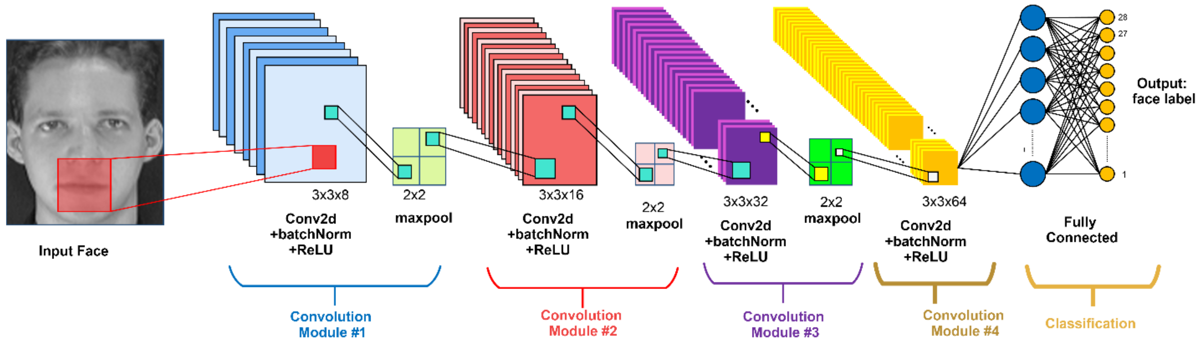

Figure 3.3 CNN Layered Architecture for ORL Dataset

IV. EXPERIMENTAL RESULT ANALYSIS

Theproposed algorithm for face recognition developed in this work has been tested on ORL face datasets. For experiment the ORL facedatasets has 280 face imagesof 28 persons having 10 imagesof each class.

Figure 4.1 Facesamples in ORL dataset of 28 different persons

For experimental evaluation different training percentage has been taken to get the best performanceof the recognition system. The benchmarksareshown in termsof Accuracy (%), Mean, and Standard Deviation.

$$SD = \sqrt{\frac{\sum |x-\mu|}{N}}$$

whereΣ = sum of, μ = dataset mean value, x = a value in the dataset, and N = number of datapoints in thepopulation.Regarding theaverage value, the following mathematical formula was used for thearithmetic mean:

$$M = \frac{1}{n}\sum_{i=1}^{n} x_i$$

M =Arithmetic mean

n = Numberof termsaveraged

x_i =Valueof each item in theaveraged numbers

Accuracy (A) iscalculated using following formula:

$$A = \frac{1}{k}\sum S_m$$

Where$k$ = number of test samples, S_m = correctlyclassified samples.

Table4.1: Comparison of The Accuracy Performance under Different % of Training Dataset (ORL Dataset)

Method	***Percentageof the training dataset***					
	66%	***67%***	***68%***	***69%***	***70%***	***80%***
DCN [18]	89.8	88.4	87.3	89.2	87.5	89.8
Two branchesof CNN [19]	91.6	90.4	91.6	92.7	90.4	92.7
LLRLCR [20]	89.5	90.5	88.5	90.5	91.4	91.4
ESPCN+CNN [1]	92.5	91.6	93.5	91.5	92.1	93.5
Proposed	***94.05***	***94.05***	***96.43***	***94.05***	***95.24***	***94.64***

Table 4.2: Mean and Standard Deviationsof All Methods (ORL Dataset)

Method	***Mean***	***Standard Deviations***
DCN [18]	88.44	1.07
Two branchesof CNN [19]	91.34	0.97
LLRLCR [20]	90.08	1.11
ESPCN + CNN [1]	92.24	0.81
Proposed	***94.74***	***0.56***

The ORL face dataset isseparated into twoparts 66% and 34%. 66% of faces datasamples used for training CNN and 34% facesare used for validation of trained network for checking and increasing accuracy. Subsequently thisstep is repeated for different training percentageand validation parts. After training and validation achieved accuracy results for different training percentage isshown in Table 4.1. Averageaccuracyand standard deviation areshown in Table 4.2.

V. CONCLUSION

This research work of face recognition is developed using convolutional neural network, having several hidden layersconstituted in 4 modules for ORL dataset for small number of facesamples. Thisscheme utilizes the minibatch operation along with batch normalization and linear rectified unit and pooling operation in each of the module toachieve higher accuracy level asseen in thesimulation outcomes. Theaccuracy level achieved for ORL face dataset averageaccuracy is 97.74% considering 66% to 80% training sets. These resultsclearlyshow the better accuracy than the benchmark methodsshown in experimental results.

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