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Development of an Illumination Invariant Face Recognition System

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ABSTRACT

The Face recognition systems have gained much attention for applications in surveillance, access control, forensics, border control. Face recognition systems encounter challenges due to variation in illumination, pose, expression, occlusion and most importantly, aging. The effect of the intensity of light on recognition image in contract with gallery image significantly affect the face recognition system. In this study, an illumination invariant Face Recognition System is developed using a 4-layered Convolutional Neural Network (CNN). The proposed system was able to recognize the different degree of face Illuminated image, thus making the model Illumination Invariant Face Recognition system. The variations caused by illumination was modelled as a form of light varying noise, and it was validated by computing its error statistics and comparing its performance with existing models found in literature. The result of the study showed that an adaptive and robust face recognition system that is illumination invariant could be achieved with CNN. The recognition accuracy achieved by the study was 99.22% with five (5) epochs and iteration of 85.

Key words: Face recognition, Illumination, Convolutional Neural Network and Dataset

1. INTRODUCTION

The main objective of a biometric system is to accurately identify individuals. This implies that biometric systems must have low recognition error rates. Face recognition over the last decade has become an area of interest for many researchers because of its wide range of applications [1]–[4]

Face recognition systems are adversely affected by light variations. The light variation factor could compromises recognition accuracy in face recognition systems. Illumination, as it affects the facial recognition system, has become a hotbed for researchers in the area of image processing and computer vision [5]–[8]. A robust Facial recognition system capable of adapting to variations in the face is necessary to curb the adverse effects of illumination on facial recognition systems. This will reduce the need for re-enrolling individuals and the cost of infrastructure procurement in the long run. In this study, a robust facial recognition system capable of adapting to variations due to trait aging in individuals using Convolutional Neural Networks is considered.

The proposed system was able to recognize/identify face trait of individuals across illumination groups. The variations caused by illumination are modelled as a form of time-varying noise and it was validated by computing its error statistics and comparing its performance with existing models found in literature. The system was able to adapt to changes in facial features as individuals face illuminate. Face detection, pre-processing and feature extraction was done using a 4-layer convolution network of size 3×3, each having 5, 10, and 50 kernels respectively. Dimensionality reduction was done using the pooling layers of the network while face recognition was done using the fully connected layer of the CNN with a Softmax classification function. Training was done using Stochastic Gradient Decent with Momentum (SGDM). The system accepted input images of size 180×200×3 obtained from a moderate trait aging dataset that belonged to the university Essex, United Kingdom. Simulation was done using the MatConvNet toolbox in MATLAB R2017b.

The paper is organized thus, a brief review of existing literature on adaptive illumination invariant face recognition systems is given in the section two (Literature Review). A thorough expository on the methodology used for the study is given in section three (Methodology). The results of the study are elucidated in section four (Results and Discussion). A conclusion is made and all parties involved in the success of the study are acknowledged. A list of references is given to close the study.

2. RELATED WORKS

Use The human face is made up of layers of muscles, skin and tissue that reside above the bones of the face. The face keeps changing after birth, and its growth is widely affected by environmental factors such as body weight, lifestyle, sunrays, smoke and the type of food being consumed by an individual. The facial muscles may differ in their control, position, form and presence. Facial characteristics of individuals changes with increase in age [9]–[13].

Illumination variation distorts the elasticity of the skin. However, the face is mapped with representations that are rapid and remain permanent. The illumination features can be represented using Active Appearance Models (AAMs). AAMs extract the global features of the face using statistical and appearance models. They are limited in functionality because they do not consider the local features of the face embedded in lighting distortions [14]–[18].

The use of coordinate transformations for modifying the structure of biological organisms so as to synthesize a structure of similar but different organisms was proposed by [7]. As a result of the investigation of the application of coordinate transformations was employed by some scientist [7]. This was a trial to imbibe age-associated alterations to the face. These scientists came up with two of such transformations which comprise Cardiodal Strain and shear transformations. The former was effective for changing the detected face age.

Further work was done shows that by the applied to 3D facial data. However, the method only created room for the manipulation of the shape of the face. It was oblivious to how variations in facial colour could be solved [19]–[21]. Okokpujie et al., also attempted the simulation of age and illumination effects on the basis of shape and colour detail. Various face composites obtained from several age groups and caricature algorithms were utilized to investigate the aging and illumination processes. The authors concluded that the subjects' perceived age (blended images) utilized for producing respective composites does not change with respect to the real age employed in producing respective composites. This means that illumination data for each group is reserved through the blending process [22]–[29]

3. MATERIALS AND METHODS

The proposed system used Convolutional Neural Network (CNN) for pre-processing, feature extraction and face recognition. It used Softmax operator as the classifier. The proposed system used a moderate aging dataset set obtained from the University of Essex, United Kingdom to train the network. The dataset contained 395 individuals with 20 images per person making a total of 7,900 images. It contained both female and male subjects with ages ranging from 18 to 20 years. It also contained images of some older individuals. The system was implemented using the MatConvNet toolbox which comprises a library of MATLAB functions implementing convolutional neural network architectures for computer vision applications. Figure 1 shows the flow chart of the implemented system. Face recognition and classification of the input image was done using the fully connected layers of a convolutional neural network. The fully-connected layers of the network were utilized for learning the classification function. The output was classified using Softmax layer, a probability distribution function which gives the top three probabilities of the input from which the output with the greatest probability is identified as the input image. The proposed system uses a CNN architecture shown in Figure 2.

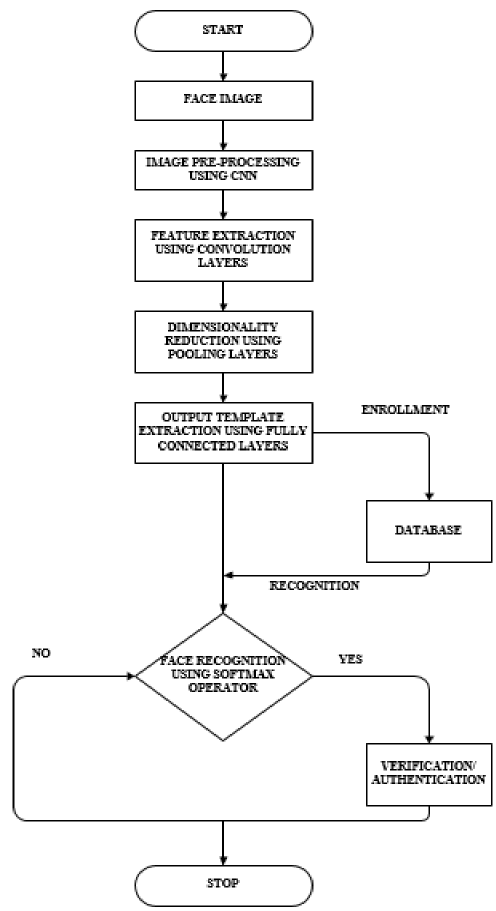

Figure 1: Flow chart of Illumination Face Recognition System

It has an input layer size of 180x200x3, three groups of convolutional layers, an activation layer (ReLU) and a pooling layer, followed by a fully connected layer of size 152 and a Softmax classification layer. The Input to the CNN is an image from the dataset. The Convolutional layers are responsible for optimum feature extraction while the pooling layers perform dimensionality reduction. The three Convolutional layers use 5, 10 and 50 filters each of size 3x3 respectively. Each pooling layer uses a filter of size 2x2. The fully connected nodes represent the total image classes in the dataset.

The images in the database used for training and testing were face photographs obtained from undergraduate students of the University of Essex taken in a controlled environment of different illumination, pose, expression and age. Some of the samples are shown in Figure 3.

CLASSIFICATION LAYER
SOFTMAX LAYER
FULLY CONNECTED LAYER (152)
POOLING
ReLU LAYER
CONVOLUTIONAL LAYER (3x3, 50)
POOLING
ReLU LAYER
CONVOLUTIONAL LAYER (3x3, 10)
POOLING
ReLU LAYER
CONVOLUTIONAL LAYER (3x3, 5)
IMAGE INPUT LAYER (180x200x3)

Figure 2: CNN Architecture of Illumination Face Recognition System

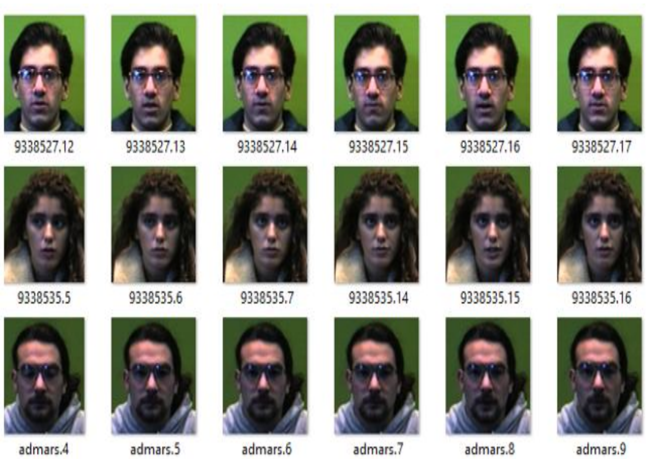

Figure 3: Sample Faces from Database

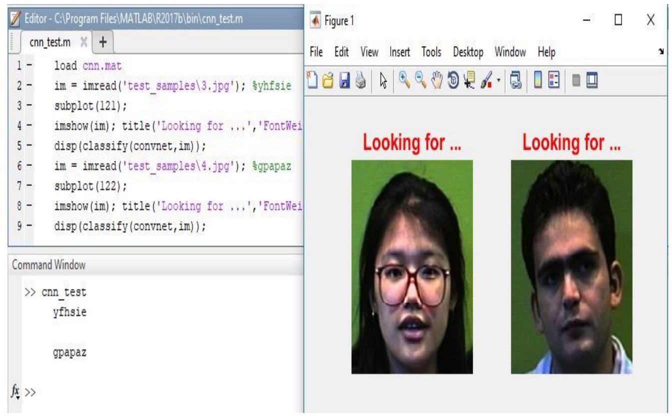

Figure 4: Testing Process 1

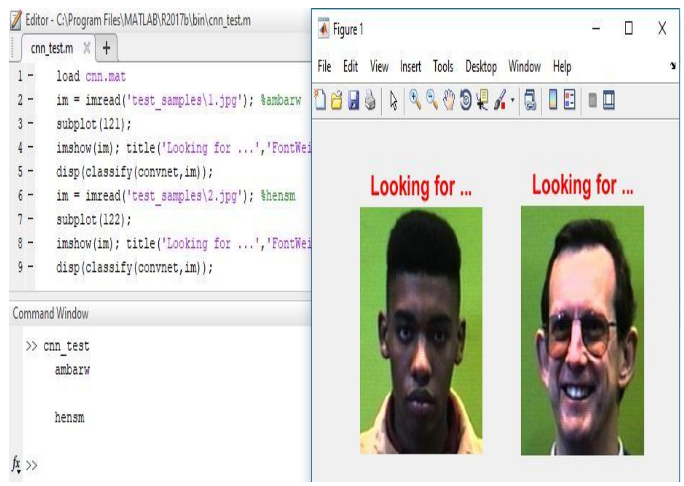

Figure 5: Testing Process 2

4. RESULTS AND DISCUSSION

The face recognition system is developed using MATLAB programming language. The output of the training and testing process is shown in the Figure 6 and Algorithm 1. During pre-processing, each subject was scaled to 180×200. The images were partitioned in the ratio, 15:5 for training and testing respectively. When the system executes, the subjects in the training database were trained in min-batches. Training was done on the mini-batches and stopped when a new accuracy was obtained. Finally, the system selects an image to be tested which displays the user ID identical to the ID tag for each subject. The system was tested with multiple numbers of new subjects. The analysis of the number of epoch and average training time is shown Table 1.

The accuracy report showed that only a few epochs are needed to train the images in the database. Five epochs and 85 iterations were used. The system was able to classify images as either known or unknown with a 0.01learning rate.

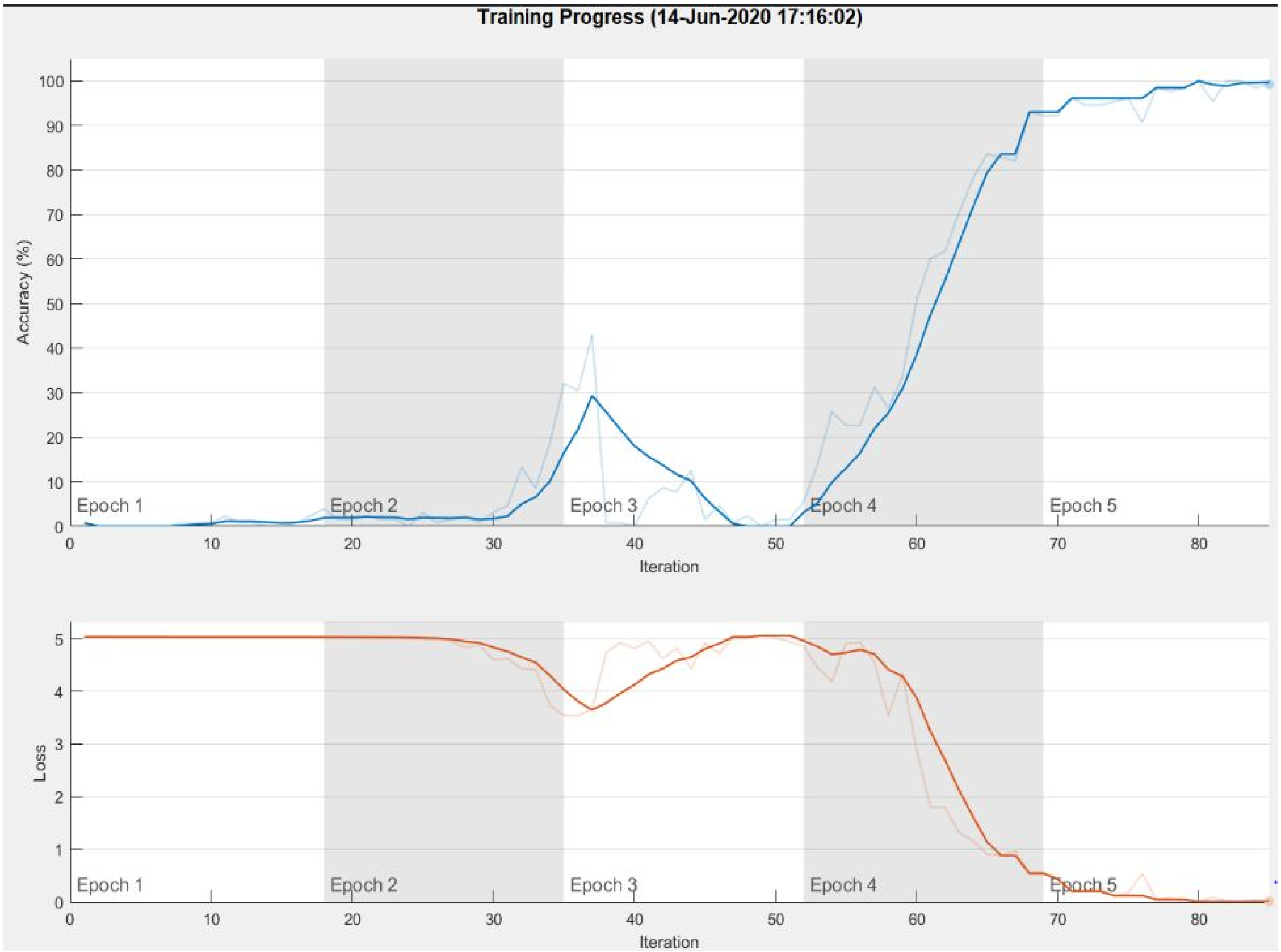

Figure 6: Training Progress of Illumination Invariant Face Recognition System

Table 1: Accuracy Report of the Illumination Invariant Face Recognition System

Training on single CPU.
Initializing image normalization.

Epoch	Iteration	Time Elapsed (seconds)	Mini-batch Loss	Mini-batch Accuracy	Base Learning Rate
1	1	18.79	5.0253	0.78%	0.0100
3	50	742.73	5.0062	1.56%	0.0100
5	85	1247.57	0.0149	99.22%	0.0100

CNN successfully trained with accuracy = 98.29
CNN successfully testing with accuracy = 99.22

The average training time increased as the network grew, but in this case 20 minutes 50 seconds. This implied that an architecture with more hidden layers would drastically increase the training time. The result showed that the proposed illumination invariant face recognition system had a testing accuracy of 99.22%. Table 2 shows the parameters and results of the experiment.

Table 2 : Parameters / Results Table

Results	
Validation accuracy:	N/A
Training finished:	Reached final iteration
Training Time	
Start time:	14-Jun-2020 17:16:02
Elapsed time:	16 min 9 sec
Training Cycle	
Epoch:	5 of 5
Iteration:	85 of 85
Iterations per epoch:	17
Maximum iterations:	85
Validation	
Frequency:	N/A
Patience:	N/A
Other Information	
Hardware resource:	Single CPU
Learning rate schedule:	Constant
Learning rate:	0.01

5. CONCLUSION

An illumination invariant face recognition system using convolutional neural networks has been was developed. The facial recognition system was invariant to changes in the face because of illumination. The system is built on a four-layered CNN.

Algorithm 1

```
datasetPath = fullfile('faces94_all');
data = imageDatastore(datasetPath, ...
    'IncludeSubfolders',true,'LabelSource','foldernames');

trainingNumFiles = 15; %15 out of 20 images of each person are used to train, 5 for testing
rng(1) % For reproducibility
[traindata,testdata] = splitEachLabel(data, ...
                        trainingNumFiles,'randomize');

% Define the convolutional neural network architecture.
layers = [  imageInputLayer([200 180 3]) %input image size 200x180x3
          convolution2dLayer(3,5)
          reluLayer
          maxPooling2dLayer(2,'Stride',2)
          convolution2dLayer(3,10)
          reluLayer
          maxPooling2dLayer(2,'Stride',2)
          convolution2dLayer(3,50)
          reluLayer
          maxPooling2dLayer(2,'Stride',2)
          fullyConnectedLayer(152) %number of persons/outputs/classes 152
          softmaxLayer
          classificationLayer()];

options = trainingOptions('sgdm','MaxEpochs',5, ...
    'InitialLearnRate',0.01, 'Plots','training-progress');

convnet = trainNetwork(traindata,layers,options);
YTest = classify(convnet,testdata);
TTest = testdata.Labels;
confMat = confusionmat(TTest,YTest);
accuracy = sum(YTest == TTest)/numel(TTest);
fprintf('CNN successfully trained with accuracy = %f \n\n',accuracy*100);

disp('Testing the CNN now..')
im = imread('test_samples\1.jpg'); %ambarw
subplot(121);
imshow(im); title('Looking for ...','FontWeight','bold','Fontsize',16,'color','red');
disp(classify(convnet,im));
im = imread('test_samples\3.jpg'); %yfhsie
subplot(122);
imshow(im); title('Looking for ...','FontWeight','bold','Fontsize',16,'color','red');
disp(classify(convnet,im));    \textbf{}
```


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