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Face Recognition with CNN and Inception Deep Learning Models

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Abstract— In this work, deep learning methods are used to classify the facial images. ORL Database is used for the purpose of training the models and for testing. Three kinds of models are developed and their performances are measured. Convolutional Neural Networks (CNN), Convolutional Neural Network Based Inception Model with single training image per class (CNN-INC) and Convolutional Neural Network Based Inception Model with several training images per class (CNN-INC-MEAN) are developed. The ORL database has ten facial images for each person. Five images are used for training purpose and remaining 5 images are used for testing. The five images for the training are chosen randomly so that two sets of training and testing data is generated. The models are trained and tested on the two sets that are drawn from the same population. The results are presented for accuracy of face recognition.

Keywords—Convolutional Neural Networks, Inception Models, Face Recognition.

I. INTRODUCTION

CNNs are very popular models in the domain of computer vision. The CNN models have its foundation from the visual systems's structure [1]. The models have the structure defined as per the local connectivity between the neurons. These local connectivity between the neurons are hierarchically organized for the image transformations [2]. The present CNNs were designed by Yann LeCun and his collaborators. They have employed the error gradient techniques to get more accurate results for variety of pattern recognition cases [3-5].

The CNN has basically three layers:

1. Convolutional layer
2. Pool Layer
3. Fully Connected Layer

Convolutional layer utilizes a kernel to convert an image into feature maps. The process of converting the image into feature maps is called Convolution. The kernel is not fixed and many kernals can be used get feature maps. The convolution process has many advantages over the fully connected layers and hence many optimal methods are developed [6-7]. When the data is in two or three dimensional form, CNNs have found its application over the fully connected neural networks. The convolutional layer has very significant effect on the depth of the volume of data.

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The purpose of the pooling layers is to reduce the size of the input volume for the next convolutional layer. It has no effect on the depth dimension of the volume of the data. As this step involves reduction in the data, it can be treated as loss of information. Hence this step is also known as Subsampling or Downsampling. The subsampling is one way advantageous for the model as it reduces the computational load on the processor. The information loss must be as low as possible. This also helps in in reducing the effect of overfitting. Subsampling can be implemented with Max Pooling or Average Pooling. A detailed mathematical framework for the max pooling and average pooling is presented in [8]. It is shown in [9] that max pool layers has faster convergence rates than average pool layers. Also there are other kinds of pooling, namely, stochastic pooling [10], spatial pyramid pooling [11, 12], and def-pooling [13].

Following a set of convolution and pooling layers, the data present in the 2 dimensional form is converted into a one dimensional vector by flattening the data. The one dimensional vector is input to the fully connected layers. Each neuron in the fully connected layers is connected to all the neurons in the preceding and succeeding layers. The fully connected network has an output layer at the end that classifies the data into several classes [14, 15].

The application of CNNs for face recognition is unique in terms of implementation vis-à-vis other face recognition methods [16-19]. In the traditional methods like PCA, LBP or ICA, the features are extracted into a lower dimensional space and the classifier uses those feature for classifying the images. Introduction of CNN in face recognition has brought a significant shift in the way the features are extracted. The first research work that employed the CNN for the purpose of face recognition can be found in [20]. The state of the art models today are light CNNs [21] and VGG face Descriptos [22]. Also the FaceNet [23] of Google and Deepnet [24] of Facebook are again based on the CNNs.

Christian Szegedy of Google has proposed a new model, namely, GoogLeNet, in 2014 in order to reduce the computational complexity of the convolutional neural networks [25]. In this new model, authors introduced inception layers in which the receptive fields of various kernel sizes were used. GoogLeNet improved this further by adding several inception blocks. The difference was to introduce the 1x1 kernel in the convolutions. With addition of kernels, the dimensionality reduction is achieved before the computationally expensive layers. The GoogLeNet has a total of 22 layers with 7M parameters, whish is far less than AlexNet or VGG.

In the next section, the deep learnig models that are used in this research work, namely, Convolutional Neural Networks (CNN), CNN-Inception model with one image for learning (CNN-INC-SINGLE) and CNN-Inception model with a set of images for learning (CNN-INC-MEAN) are discussed in details about their architecture.IN Sec III, the simulation results are presented for two kinds of datasets that are drawn from the ORL database. Finally the conclusions are presented in Sec. IV.

II. DEEP LEARNING MODELS

In this research work, three deep learning models are used for the purpose of face recognition. The ORL database is used for the face recognition. The ORL database has images of 40 people. Hence the numbers of classes to be classified by the deep learning models are 40. This is a very challenging task as the number of classes for the high classification rate is usually binary. Sometimes, the number of classes can be just above the binary, for example, three, four or five classes. In the case of OLR databases, the number of classes is forty, which is a huge task.

In order to perform the face recognition task, three deep learning models, namely, Convolutional Neural Networks (CNN), CNN-Inception model with one image for learning (CNN-INC-SINGLE) and CNN-Inception model with a set of images for learning (CNN-INC-MEAN). The CNN-INC-MEAN model is proposed in the work to get the high accuracy in the face recognition. All these models are developed on the Keras platform that runs on the Tensorflow as the backend. The Google Colab was used as the computing platform.

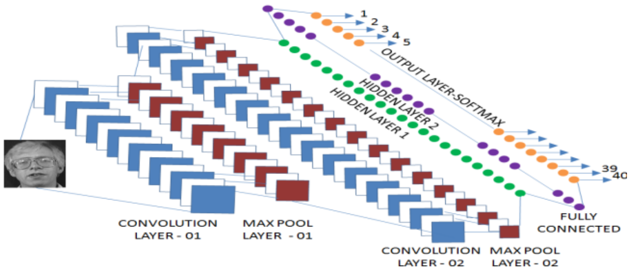

Figure 1: Convolutional Neural Network for ORL Database

Fig. 1 shows the CNN architecture used in this work for face recognition. The input image of 112x96x3 is used at the input layer of the network. The input image is convoluted with 16 filters of size 5x5 which produces the matrix if size 108x88x16. The activation function of RELU is used in the convolution. A max layer of size 2x2 is applied on the convoluted layer that results in 107x87x16 matrix. The output from the max pool layer is passed on to another convolution layer of filter size 3x3 with 32 filters. This will generate a matrix of size 105x85x32. Again the output from the convolution layer is input to another max pool layer of size 2x2 to produce a matrix of size 104x84x32. Same procedure is followed with 2 more sets of convolution and max pool layers (not shown in Fig. 1). The 3rd convolution layer has 64 filters with filter size of 3x3 and the max pool filter of size 2x2. The fourth convolution layer has 128 filters of size of 3x3 and the max pool filter of size 2x2.

The output from the max pool layer is flattened to have a vector of size 978,432. The vector is input to a fully connected layer that has two hidden layers. The first hidden layer has 128 neurons and the second hidden layer has 256 neurons. The second hidden layer is connected to the output layer which has the SOFTMAX function to classify the images into 40 distinct classes. In all layers, the RELU action function was used except for the output layer. Since there are 40 distinct classes to be classified, a SOFTMAX layer was used at the output. The Adadelta optimizer of Tensorflow, with a learning rate of 0.2 and rho of 0.9 is used to optimize the categorical cross entropy.

As a second architecture, a CNN-INC model has been developed with Keras and Google Colab as shown in Fig. 2. The CNN-INC model has three convolutional layers at the beginning. The first and third layers have the max pool layers after the convolution layer. The output from the max pool layer of the 3rd convolution layer has been input to inception layers. The inception layers are again defined with the convolution layers and the max pool layers as shown in Fig. 2. The convolutions are 1x1, 3x3 and 5x5. Additionally the same input is also input to a max pool layer. Each inception block has some or all of the 1x1, 3x3, 5x5 convolution and max pool layers. The same input is processed in several inception layers in series.

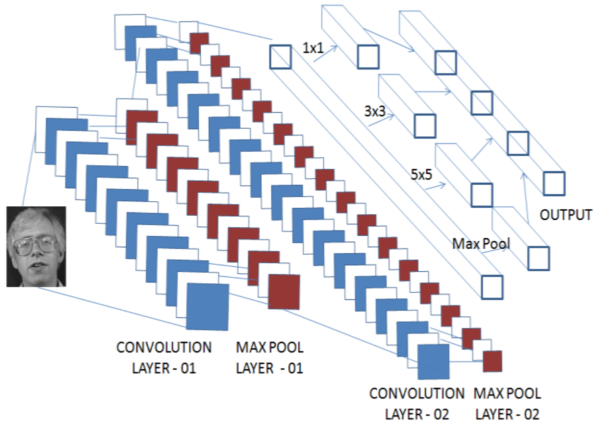

Figure 2: CNN-INCEPTION model for ORL Database

Finally, the output from the inception block is flattened and input into a fully connected layer of size 128 neurons. Triplet loss function of the tensorflow is used as the loss function. The initial weight for the inception model has been used from the GoogLeNet model [25]. The CNN-INC model has been input with the face images of the ORL and the model outputs the 128 encoding for each of the image./ The training is performed by predicting the encodings from the CNN-INC model for each of the image in the training data set. For example, in the CNN-INC model, only the first image is used to determine the encodings for each person. When the test data is presented to the model, each image in the test set is again converted into the encodings by the CNN-INC model. The distance between each of the images in the training dataset is compared with that of the test image. The comparison is made by computing the distance between the encodings. The train image with shortest distance is the face recognized for the test image. The distance has a threshold value, if the minimum distance is more than the threshold value, then it is treated as an image that does not belong to the train dataset.

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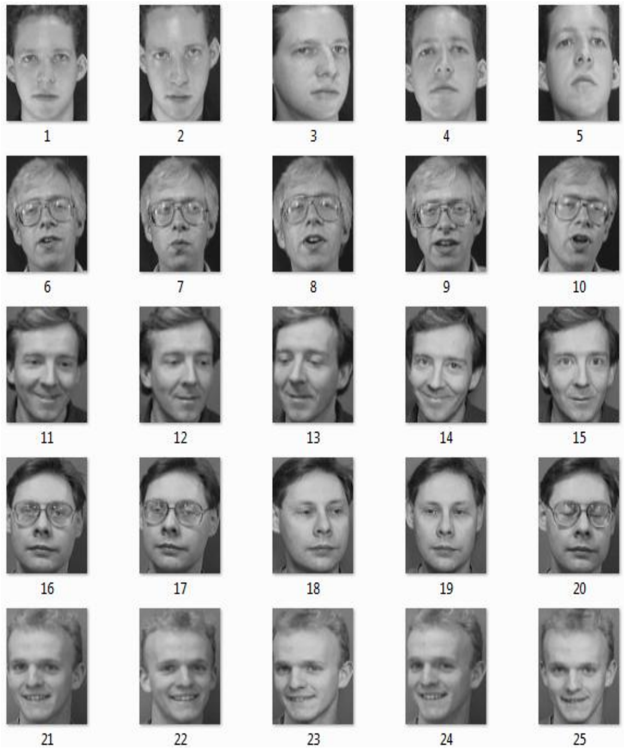
In the third model, CNN-INC-MEAN, the architecture is replicated as many times the number of observations for each class. For example, in ORL data base, the 5 images of each person is randomly chosen for the training purpose. Hence the CNN-INC-MEAN model is run five times for each person and the five sets of encodings are extracted from the CNN-INC-MEAN model. The mean values for the five encoding are computed additionally at the output of each of the image processing. In other words, the five inception models are run parallel and the outputs are processed to calculate the mean of the encodings. The mean of the encodings form the training out of the CNN-INC-MEAN model. Each of the image from the test set is now compared with the mean of the train set and the shortest distance is found. If the shortest distance is lower than a threshold limit, then the class is identified. Else, the image is declared as not part of the training set.

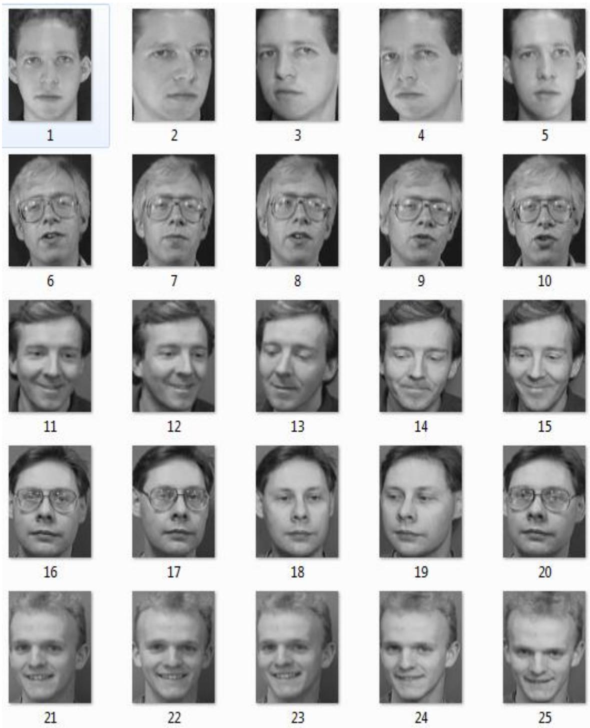
In the CNN-INC model, encodings of only one image is considered to find the matching class. The image can be different depending upon on the accuracy. In case of CNN-INC-MEAN model, a set of images can be chosen to determine the encodings that closely represents the set of images in the training set. The number of images in the training set to determine the mean can chosen to reduce the computational time for a required accuracy. Hence a trade off is needed between the accuracy and the computational time.

III. THE SIMULATION RESULTS

In this paper, the simulations are performed on the ORL database. Two datasets are created from ORL by sampling method. There are 10 facial expressions for each person. Since there are images of 40 people, a total of 400 images are present in the database. The first dataset contains facial expressions of 1,3,5,7 and 9 in train set and 2,4,6,8 and 10 in the test set. In the second dataset, the facial expression of 1,3,6,8 and 9 are used in train set and 2,4,5,7 and 10 are used in train set. Each train and test sets contain 5 facial expressions all the 40 people. Hence there are 200 images in train set and 200 images in test sets. Figs. 3 and 4 shows the sample of train and tests sets.

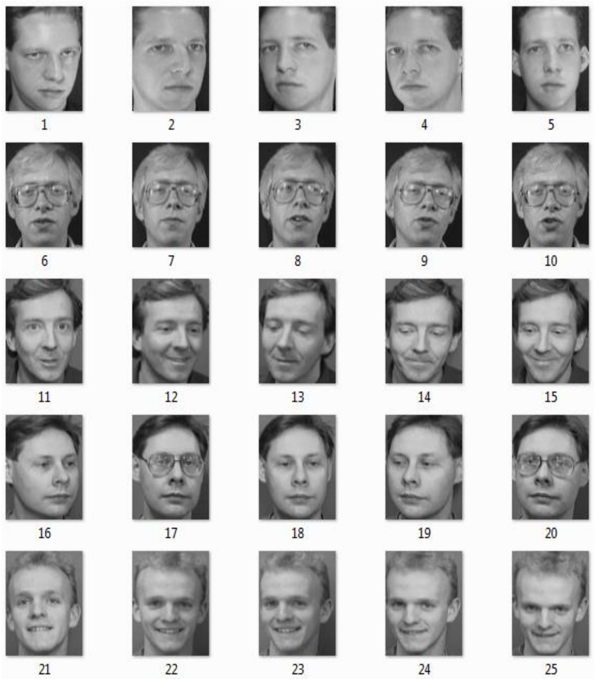


a. Train Set – 1 (Only 5 persons are shown)



b. Train Set – 2 (Only 5 persons are shown)

Figure 3: Images for training



a. Test Set – 1 (Only 5 persons are shown)

b. Test Set – 2 (Only 5 persons are shown)

Figure 4: Images for testing

As a first model, the CNN model was trained using the face images of 1,3,5,7 and 9 for each person. The model once trained as explained Sec. 2, is tested with the face images of 2,4,6,8 and 10. When the model was trained, the loss function and accuracy was plotted as an output. The model was run with a total of 20 epochs. It can be noticed from Fig. 4 that the accuracy has reached maximum of 1.0 for training set at epoch 10. The accuracy has gradually increase and reached maximum at epoch 10 and there is no improvement thereafter.

Since from Fig. 5, it can be observed that the loss has dropped significantly in the first epoch itself and the reduction in loss was very gradual until 7^{th} epoch. Thereafter, the loss function became slowly flat and after 10^{th} epoch, there is no improvement. Hence the model is assumed to have converged at 10^{th} epoch

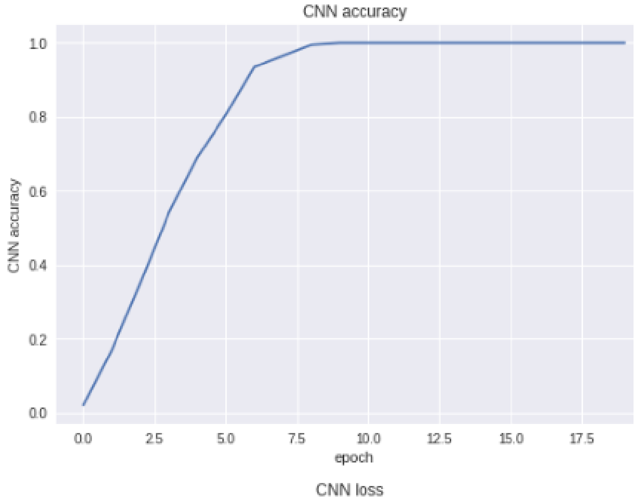


Figure 5: Accuracy during CNN-training for Train Set 1-3-5-7-9

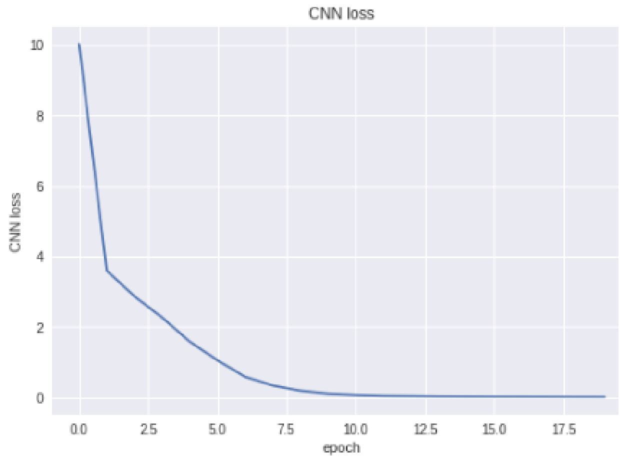


Figure 6: Entropy Loss during CNN-training for Train Set 1-3-5-7-9

Table

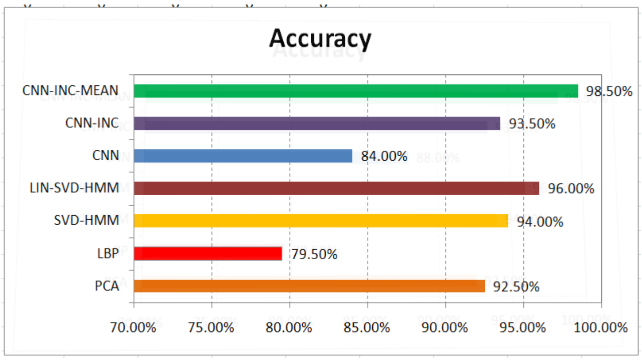


Figure 7: Accuracy of LBP, PCA, HMM and CNN based Deep Learning Models for Train Set 1-3-5-7-9.

Fig. 7 shows the percentages of the correct match made by various methods for the train and test data sets as defined above.

The train dataset has the facial expressions of 1,3,5,7, and 9; and test set has the facial expression of 2,4,6,8 and 10. A total of 7 face recognition methods are chosen to test the accuracy of the models for this combination of train and test sets. The models are PCA, LBP, SVD-HM, LIN-SVD-HMM, CNN, CNN-INC, and CNN-INC-MEAN. It can be observed that PCA and LBP are traditional statistical models for the face recognition, whereas SVD-HMM and LIN-SVD-HMM are statistical sequence models and CNN, CNN-INC and CNN-INC-MEAN are deep learning models. The mathematical back grounds of each of these three models are quite different from each other. In this research work, an attempt is made to compare the performance of the models for a given dataset.

It can be observed from Fig. 7 that, LBP has performed very poor. Though the LBP is very robust, it did not perform well in this case due to the reason that the data set has lot of diversity at the local feature level. Since each of the facial expression is different in training as well as test sets, the local feature of quite different from one image to another image of the same person. Hence the accuracy was very poor. The PCA and HMM based models are discussed in detail in ref [3].

The next model that has a better accuracy is CNN model. It is a deep learning model. The deep learning models perform very well when the numbers of classes to be classified are just two. As the number of classes increase beyond two, the accuracy of the deep learning models comes down. In the present case, the number classes are 40 which is the number of distinct persons to be identified. The reason for this kind of behavior is a person is classified by computing the probability of match in the soft max layer. If there are only two classes, then any person with probability more than 0.5 is a correct guess and less than 0.5 is a wrong guess, for example. The threshold need not be at 0.5, but can vary depending up on the accuracy needed. In the present case, there is high possibility of getting some of the 40 probabilities very close to each other. Hence it becomes very difficult to correctly classify the images for the algorithm.

The CNN model can be improved by adding inception blocks to the CNN layers in place of the fully connected neural networks. This is a transfer learning based model. The weights of this model are initialized from the Google Inception model for image classification. When each image of the train set is input this model, it creates the encoding of the image. When each of the five facial expression of each person in the test set is passed through the CNN-INC model, it creates the encodings of each image. It computes the distance of each image in the data set with encodings of one image of each person. The image with shortest distance is treated as recognized image. If the shortest distance is more than the threshold, it is considered as image not found in the train dataset. In the present model, a threshold value of 0.7 is set. With this approach, the model has classified the faces to 93.5%. That means out of 200 test faces, 187 faces are correctly recognized.

To improve the CNN-INC model, a new method is proposed in this work where instead considering just one image for training purpose, a set of images are considered. The encodings are averaged over the set of images after the training.

When 5 images are considered for the training purpose, the accuracy has improved significantly from 93.5% in CNN-INC model to 98.5% in CNN-INC-MEAN model. This is due to the reason that the 5 different facial expressions represent a good dataset of many facial expressions. Hence the CNN-INC-MEAN model is considered to be the best model among all the other models tried in this research work.

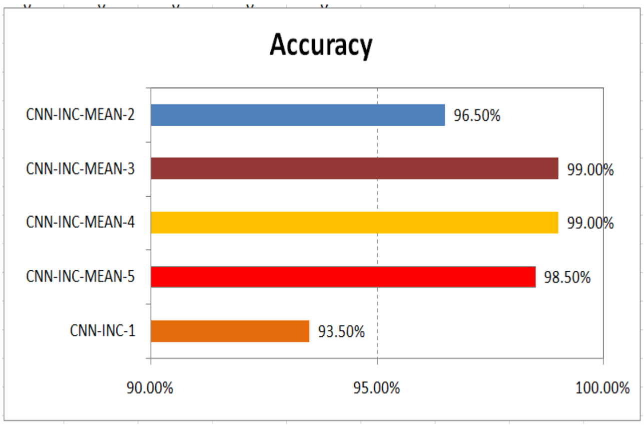


Figure 8: Accuracy of CNN-INC-MEAN models for Train Set 1-3-5-7-9

As next step, another experiment is conducted to determine the number of facial expressions required to highest accuracy. The experiment stated with just one facial expression, as mentioned above. The accuracy was found to 93.5%. When the number of facial expressions is increased to two to calculate the mean encodings, the accuracy improves to 96.5%. When the number of facial expression used for the mean encodings computation was increased to 3 and 4, the accuracy was at maximum of 99%. Hence by adding more facial images beyond 3 in this case was not useful. In fact, by adding more images, the mean gets shifted from its optimal position. The number images required for the optimal mean can be only tried by trial and error for each dataset separately.

As a next step, the training and test sets are shuffled in order to test the robustness of the model. A train set is created with the facial expression 1,3,6,8 and 9 and test set is created with facial expressions 2,4,5,7 and 10 from the ORL database. The three models, namely, CNN, CNN-INC and CNN-INC-MEAN are run with the new datasets.

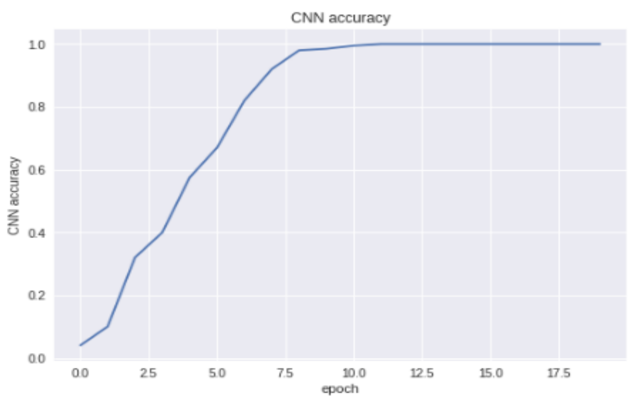


Figure 9: Accuracy during CNN-training for Train Set 1-3-6-8-9

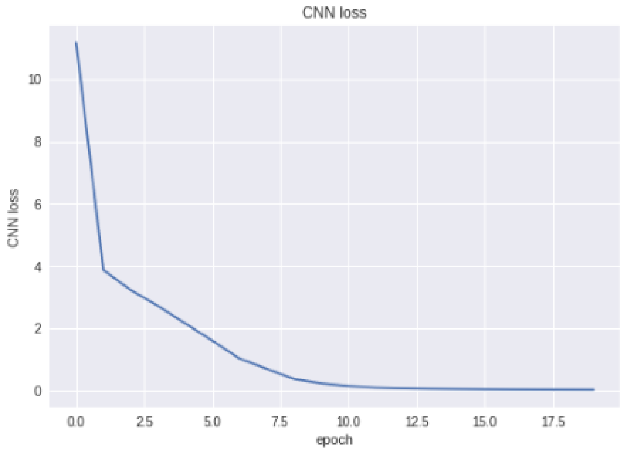


Figure 10: Entropy during CNN-training for Train Set 1-3-6-8-9

It can be noticed from Fig. 9 that accuracy has gradually increased and becomes maximum at epoch 12. The accuracy remains stable after 12 epochs. Similarly the entropy loss does not reduce after 12 epochs. There is a significant reduction in the entropy loss in 1st Epoch. The reduction in loss was gradual until 9th epoch and it becomes very slow after 9th epoch until 12th epoch.

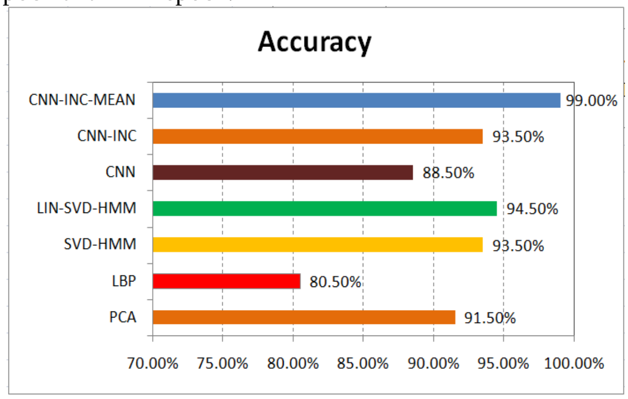


Figure 11: Accuracy of LBP, PCA, HMM and CNN based Deep Learning Models for Train Set 1-3-6-8-9.

From Fig. 11, it can be observed that the CNN model has yielded 88.5% accuracy for the train set 2 (1-3-6-8-9) compared to that of train set 1 (1-3-5-7-9), where it was at 84%. The CNN-INC has yielded same level of accuracy for both the training sets. In case of CNN-INC-MEAN, the accuracy stands at 99% for the train set 1-3-6-8-9 compared to that of train set 1 (1-3-5-7-9), which is at 98.5%. The CNN-INC models have produced almost same level of accuracies for both the train sets. The CNN-INC-MEAN model has used all the five facial expression to compute the mean of the encodings.

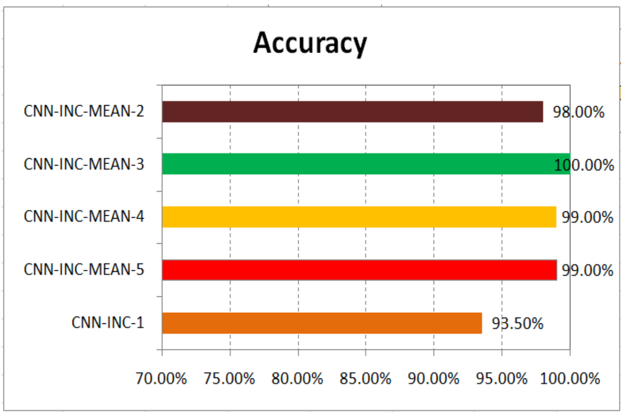


Figure 12: Accuracy of CNN-INC-MEAN models for Train Set 1-3-6-8-9

By observing Fig. 12, it can be concluded that when the first three images (1-3-6) are considered to compute the mean encodings, the accuracy is at 100%. This is the best from the CNN-INC models. By further increasing the number of images into the computation of mean encodings beyond 3 is not useful as already observed with the train set 1. The second experiment corroborates the fact that for the ORL data sets, by considering the three images in the train set yields the maximum performance.

IV. CONCLUSION

In this research work, the ORL database has been tested for the performance by three models, namely, CNN, CNN-INC and CNN-INC-MEAN. The CNN is a standard model and with the both the samples of data sets, the accuracy produced was 84 and 88%. When the CNN-INC model was used which is based on the transfer learning inception model, the accuracy was 98.5% for both the datasets. When the CNN-INC-MEAN was used the accuracy stood at 98.5 and 99% for the two datasets, which is highest among all the methods presented in this paper. Further another experiment was carried out to determine the optimum number of facial expressions to be considered in calculating the mean of the encodings to get the maximum accuracy. When number of facial expression as three, the accuracies of the two datasets were 99% and 100% respectively. This is the best that can be obtained for the ORL dataset compared other methods presented in this paper. It is also shown that by increasing the number of facial expression beyond three, does not improve the accuracy or add only additional burden to the computations. Hence the optimal number of observations for each person in the ORL database is three to get the highest accuracy of around 100%.

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