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Facial Expression Recognition using CNN

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ABSTRACT

People have consistently been able to perceive and recognize faces and their feelings. Presently PCs can do likewise. We propose a model which recognizes human faces and classifies the emotion on the face as happy, angry, sad, neutral, surprise, disgust or fear. It is developed utilizing a convolutional neural network(CNN) and involves various stages. All these are carried out using a dataset available on the Kaggle repository named fer2013. Precision and execution of the neural system can be assessed utilizing a confusion matrix. We applied cross-approval to decide the ideal hyper-parameters and assessed the presentation of the created models by looking at their training histories.

Keywords : Deep learning, Emotions, facial expressions, Convolutional neural networks.

I. INTRODUCTION

Facial expressions add much importance to the speech and it can be understood with no effort. They play a crucial role in non-verbal communication. Programmed acknowledgment of outward appearances can be a significant segment of characteristic human-machine interfaces. Present a methodology which identifies outward appearances is Convolutional Neural Networks (CNN). The input into our system is an image; we then use a neural network to find the facial expression which should be one these labels: anger, happy, fear, neutral, disgust, sad and surprise[2].

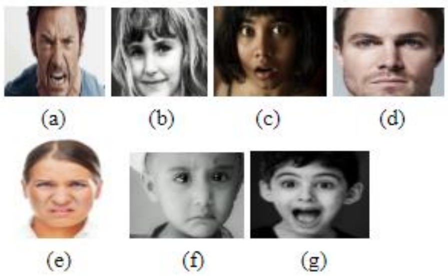

Figure 1.1: Examples of seven facial emotions that we consider in this classification problem.

(a) anger, (b) happy, (c) fear, (d) neutral, (e) disgust, (f) sad, (g) surprise

II. METHODS AND MATERIAL

Convolutional neural networks is the easiest way to detect facial expressions. Although it's accuracy and complexity may vary with other approaches, it is widely used[3]. A multilayer neural network is an arrangement of one or more convolutional layers and one or more fully connected layers is known as a convolutional neural network (CNN).

The main benefit of CNN is it can classify expressions without any human intervention. In addition to it, it is easy to train and have many fewer parameters than fully connected networks having the same number of hidden layers. Our model uses a CNN which has seven hidden layers[4] each one for the seven basic expressions viz. happy, angry, sad, neutral, surprise, disgust, fear respectively.

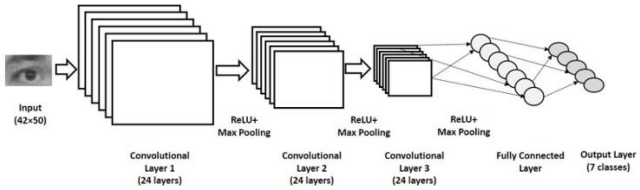

Figure 2.1: Architecture of CNN

Dataset

We used a dataset provided by Kaggle website[1], which consists of about 35,887 well structured forty eight × forty eight pixel grayscale images of faces. The images are processed in such a way that the faces are almost centred and each face occupies about the same amount of space in each image. Each picture must be ordered into one of the seven classes that express extraordinary facial feelings. These facial emotions have been categorized as: 0=Angry, 1=Disgust, 2=Fear, 3=Happy, 4=Sad, 5=Surprise, and 6=Neutral. Figure 1.1 depicts an example for each facial expression category. In addition to the image class number (a number between 0 and 6), the given images are divided into three different sets which are training, validation, and test sets. There are about 28,709 training images, 3,589 validation images, and 3,589 images for testing. The classification of the dataset into various emotions is as below:

	EMOTION	NUMBER
0	Angry	4935
1	Disgust	5472
2	Fear	5121
3	Happy	8989
4	Sad	6077
5	Surprise	4002
6	Neutral	6198

Figure 2.2: Classification of dataset

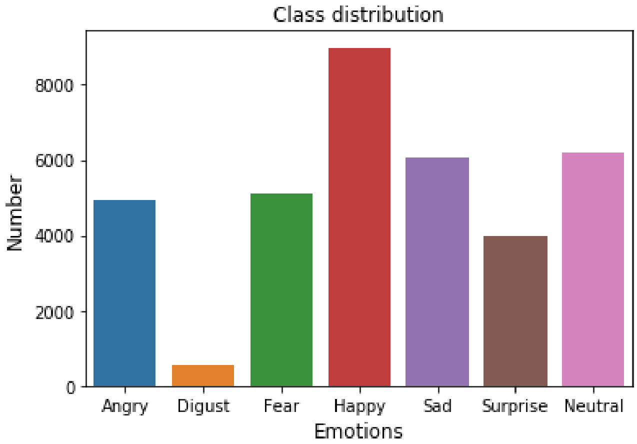

Figure 2.3: Class distribution of dataset

The first step involves extracting required information from the dataset of 35,887 samples and storing it to NumPy arrays. This is called pre-processing. During pre-preparing the dataset is part into three sections as train dataset, test dataset and validation set as shown in figures 2.4,2.5,2.6 respectively.

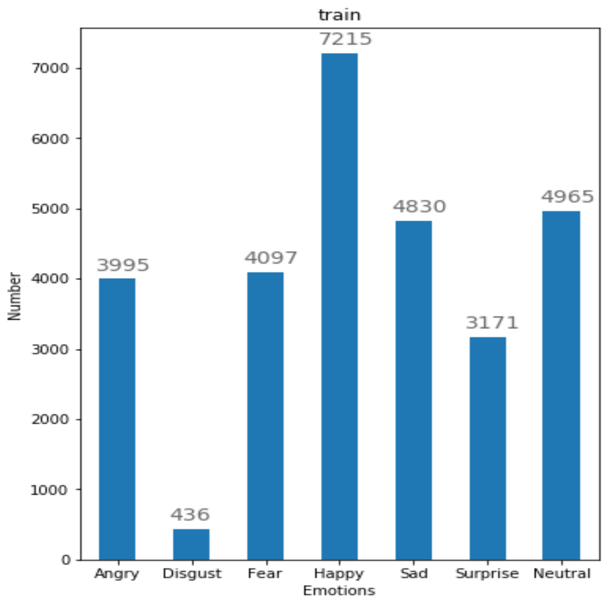

Figure 2.4: Distribution of training dataset.

Figure 2.5: Distribution of test dataset.

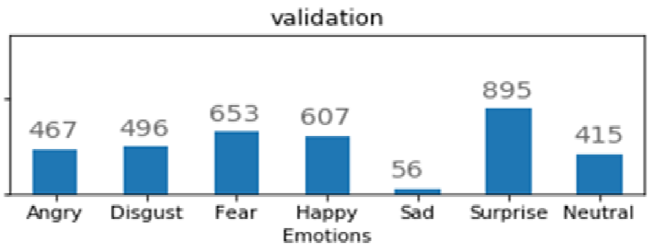

Figure 2.6: Distribution of validation dataset.

The model operates in two main primary stages: training and test. The training phase takes as input a set of images with a face, its eyes locations and expression id, and outputs the set of weights of the round that achieved the best result with the validation data after a few training rounds considering the data in divergent orders.

During the test, the system receives a grayscale image of a face along with its respective eye centre locations and outputs the predicted expression by using the final network weights learned during training.

The most significant piece of our model is building the convolutional neural system[7] through which we remove the necessary highlights to identify feeling. This process involves various steps like max-pooling, normalisation etc.

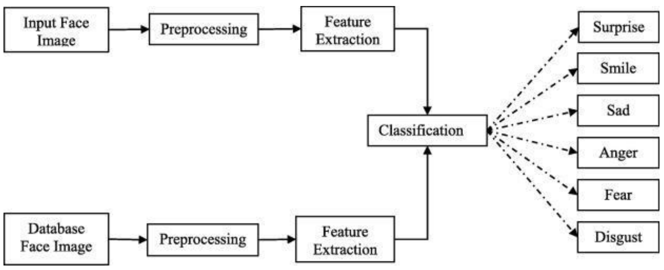

Figure 2.7: Flow of the model.

After several epochs, the model gets trained very well and the accuracy of the model can be evaluated.

III. RESULTS AND DISCUSSION

The countenances in the dataset have been naturally enlisted with the goal that the face is pretty much focused[3] and involves about a similar measure of room in each picture. Training contains two columns. The emotion section contains a numeric code running from 0 to 6 for the feeling that is available in the outward appearance picture. The pixels column contains a string surrounded in quotes which is a space-separated pixel value in row-major order. Testing contains just the pixels section and your errand is to foresee the emotion column. The output of the training phase is the set of weights of the round that achieved the best result with the validation data after a few training rounds considering data in different orders. The testing phase uses the same methodology as the training phase. Its output is a single number - the id of one of the seven basic expressions.

The expressions are represented as integer numbers (0 - angry, 1 - disgust, 2- fear, 3 - happy, 4 - sad and 5 – surprise, 6-neutral). As shown in figure 3.1, based on the integer number received the expression is displayed.

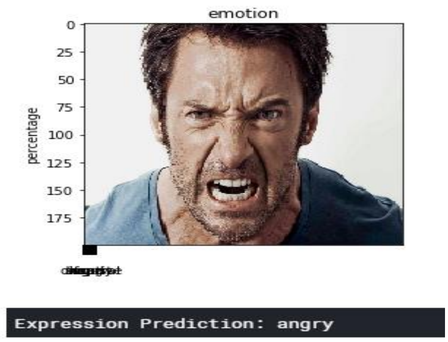

Figure 3.1: Example output for expression prediction of an image

Figure 3.2: Representing prediction of sad emotion

Furthermore, one can observe that the deep network has reduced the overfitting behaviour of the learning model by adding more non-linearity and hierarchical usage of anti-overfitting techniques such as dropout and batch normalization. Here are below the graphs related to the model accuracy and model loss based on the number of epochs.

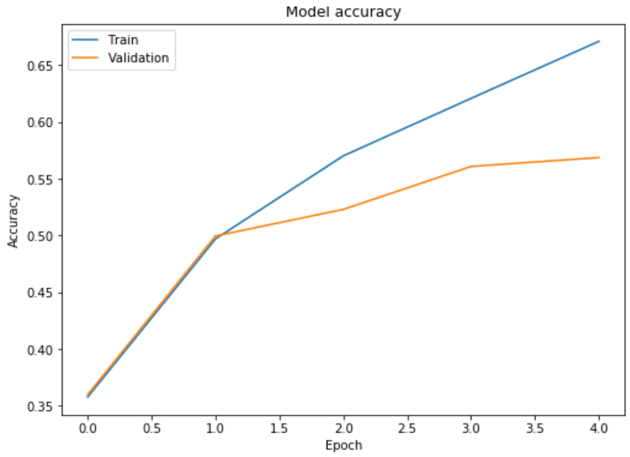

Figure 3.3: Representation of Model accuracy

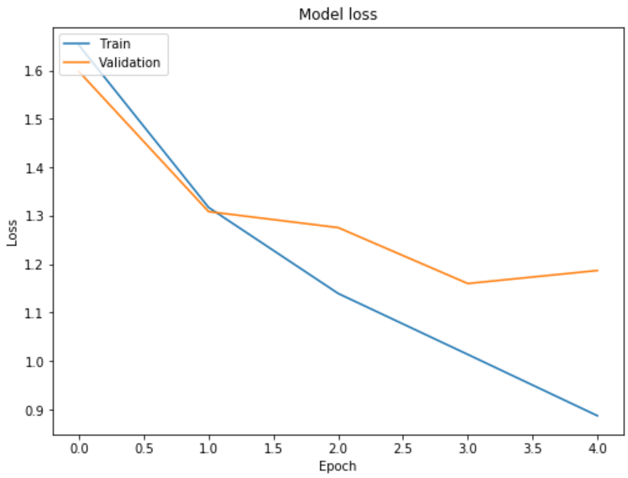

Figure 3.4: Representation of Model loss

Moreover, we computed the confusion matrices as shown in figure 3.5. A confusion matrix is a table that is regularly used to portray the exhibition of a classification model (or "classifier") on a lot of test information for which the genuine qualities are known. It allows the visualization of the performance of an algorithm. It allows easy identification of confusion between classes e.g. one class is commonly mislabelled as the other. Most execution measures are registered from the confusion matrix.

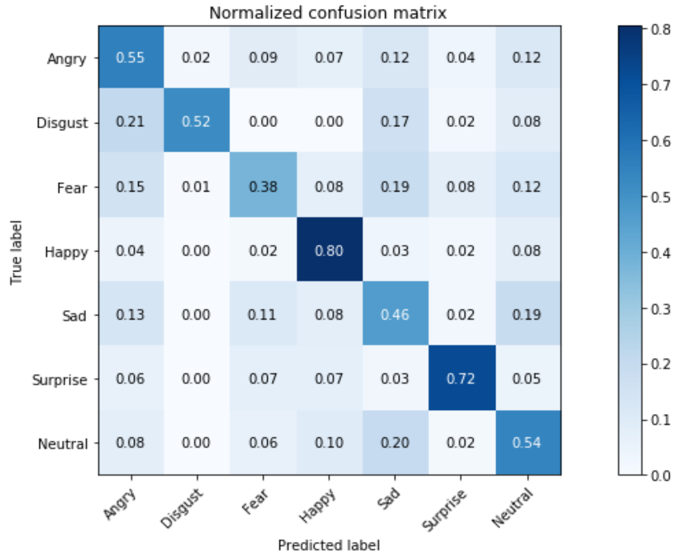

Figure 3.5: Confusion Matrix

IV. CONCLUSION

In this paper, we addressed the task of facial expression recognition and aimed to classify images of faces into any of seven discrete emotion categories that represent universal human emotions. We created different CNNs[8] for facial expression acknowledgment issue and assessed their exhibitions utilizing diverse post-handling and representation systems. The outcomes demonstrated that profound CNNs can learn facial qualities and improve facial expression recognition.
We had extended our model for more number of times (with 50 epochs). We constantly achieved our model with an accuracy ranged between 60 to 70 percentage (Our accuracy may vary in between the given limits).

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