FACIAL EMOTION RECOGNITION USING DEEP LEARNING

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Abstract:

Facial emotion recognition (FER) is an important part facial recognition which is gaining more importance and need for this is growing tremendously. There are many methods to detect facial emotions in the field of machine learning and artificial intelligence, many of them cannot give the needed accuracy so try using deep learning models. Here in this project we will use Convolutional Neural Networks (CNN) to classify facial emotions. We would implement the model using Google Colab as it provides GPU to run deep learning models. Final accuracy of this model using Convolutional Neural Networks (CNN) is 63%. Though it is not high it is better than many other models.

Keywords-Facial Emotions, CNN, Deep learning, image recognition, image classification, Machine learning, Artificial Intelligence, Model

I. Introduction

Facial Emotion or Expression Recognition has drawn the attention of researchers, as the capability of recognizing one's expressions helps in human-computer interaction. There are various ways to examine the recognition of human expressions, ranging from facial expressions, postures, voice tone etc. In this paper we have concentrated more on Facial expression recognition. Facial emotion recognition (FER) is one of an interesting research area in which a lot of advancements such as automatic translation systems, machine to human interaction are happening in industries. In this paper we will be discussing about

FER dataset, feature extraction, CNN model and accuracy. This paper is organized as follows section 2 describes background information of facial emotion recognition.

II. Background Information

A. Emotion Recognition

Facial Recognition is the technology that deals with techniques and methods to identify the emotions from facial expressions. Various technological developments in deep learning has made facial emotion recognition easier. It is expected that expressions and emotions are the next communication medium with computers in future. Need for automatic facial emotion recognition has increased tremendously in recent years. Research in this area mainly concentrates on recognizing facial emotions through photos and videos. We can also recognize facial emotions in real time also.

Facial Emotion Recognition deals with identification of emotions, techniques and methods used for emotion. Vast number of methods have been adapted to infer the emotions such as machine learning, neural networks, artificial intelligence, emotional intelligence.

B. Facial Emotion Recognition

Facial Emotion Recognition is an area which tries to identify the emotion from the facial expression. The surveys prove that the developments in emotion recognition makes the complex systems simpler. Facial Emotion Recognition has many applications which is discussed later. Emotion Recognition is the hard-headed task since emotions may differ depending on the environment, appearance, culture, face response which leads to uncertain data. Survey

on Facial emotion recognition [1] helps a lot in discovering facial emotion recognition.

C. Deep Learning

Deep Learning [2] is machine learning technique which is used to model the data that are designed to do a required task. Deep learning in neural networks has widespread purposes in the area of image recognition, classification, decision making, pattern recognition etc. Some other deep Learning practices like multimodal deep learning is used for feature selection, image recognition etc.

D. Applications of Facial Emotion Recognition

Emotion Recognition is used in various applications for identifying calls based on their emotions. Emotion Recognition aids as the identifier for conversational analysis for identifying the discontented customer. Facial Emotion Recognition is used in car boarding system dependent on data of the mentality of the driver can be made available to the system to initiate his and the safety of the customer.

III. Proposed Methodology

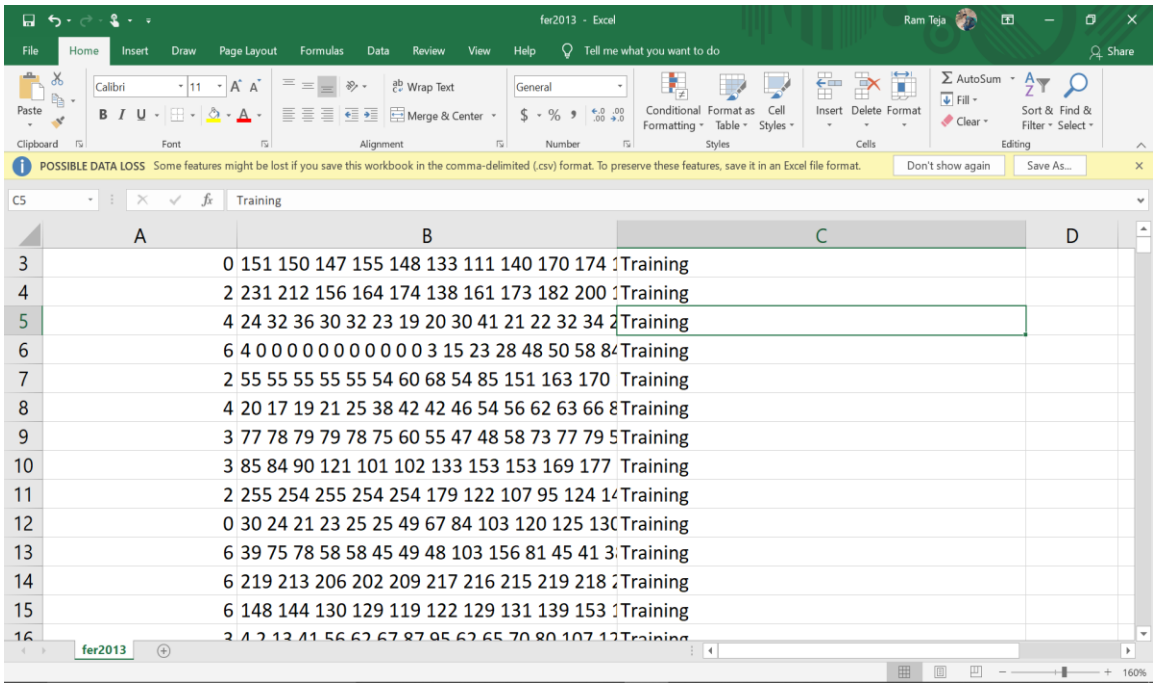
This section explains the methodology we used for this facial emotion recognition algorithm.

A. Dataset

For this problem we have used the fer2013.csv dataset to perform training and testing on the model we will be building. Our dataset has 35,887 images, which are classified into seven categories - Angry,

Disgust, Fear, Happy, Sad,

Surprise, and Neutral.



The column A is emotion (0=Angry, 1=Disgust, 2=Fear, 3=Happy, 4=Sad, 5=Surprise, 6=Neutral).

The column B is image NumPy array data of images.

The column C determines whether it is training or testing data.

B. Pre processing

We are only going to need the Class and the Image Data. Image data is one big string of numbers exactly 2304 numbers. These are pixel intensity values and each number represents the darkness of that pixel in the image. It can take any value from 0 (White) to 255 (Black). We split the string to get hold of individual numbers and then reshape it into a 48 x 48 array and dividing by 255 normalizes the data.

Once we go through all the images, we expand the

dimension of our data array by one to accommodate for the channel value. We one-hot encode the labels then return the NumPy arrays.

C. Importing Libraries

We have imported some libraries such as NumPy, pandas, TensorFlow, keras etc.

NumPy- for mathematical operations.

Pandas-for working on csv files and data frames.

TensorFlow-for using deep learning models.

Keras-To build neural networks.

D. Convolutional Neural Networks

In deep learning CNN's are a class of deep neural networks which are mostly used for image modelling and image classifying etc. They are regularized versions of multi-layer perceptrons.CNN's use very less pre-processing compared to other image or visual classification algorithms.

E. Building Model

We have built ourselves a Convolutional Neural Network which has convolutional layers armed with filters that extract features out of images.

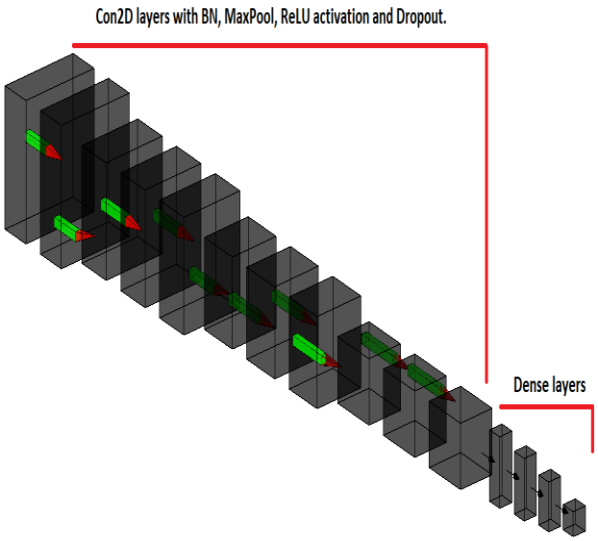
Callback functions are those functions which are called at the end of every epoch and in this model, we use two callback functions - ReduceLROnPlateau and EarlyStopping.

1.ReduceLROnPlateau:

monitors a certain variable, in this case, validation loss and alters the learning rate when the value stops significantly changing after some certain number of epochs (patience).

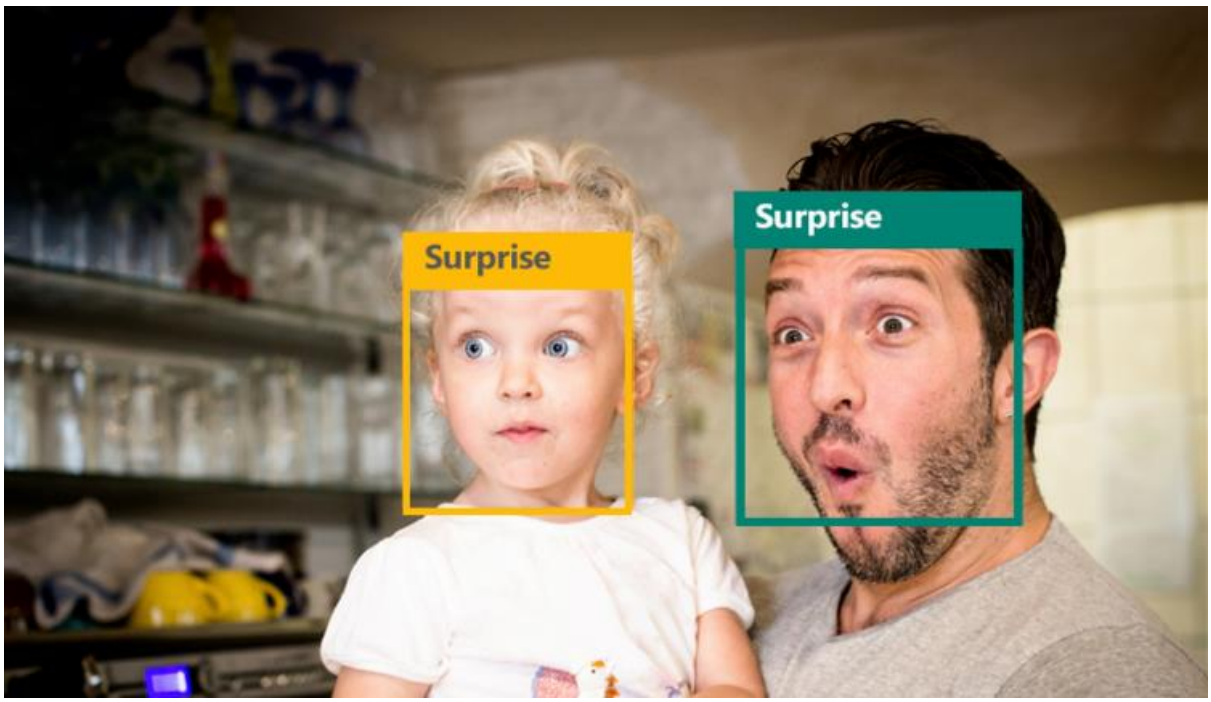
2. EarlyStopping: At times our optimiser can land in *local optima* and get stuck there. There is no point in continuing the training as there won't be any further improvements.

3. ModelCheckpoint: Saves the best version of our model along with the weights, so that in case any crash occurs, our model can be recovered.



We have used Keras to deploy our neural network and if you look at the architecture then you will notice that we have used Dropout layers frequently.

Dropout layers inhibit overfitting by randomly dropping out units from the neural network. We will use 20 percent of the training data as validation data.



IV. Experimental Setup

All the labels that are under training will be trained and size of each image is (28,28,1). While training our number of epochs are 404 if you need you can keep more or less. The batch size is 64 and learning rate is 0.01. You can see after epoch 1 the accuracy is 19.5% and loss is 2.10 and after epoch 404 the loss is 0.21 and accuracy is 93% so that we have completed training.

V. Result and Analysis

In the training the accuracy is 93% approx. But in the testing the accuracy is 63% it means the model is overfitting but it is still good accuracy compared to other models such as SVM and others. Maybe it needs more data than this to give some better accuracy

VI. Conclusion

Many researchers have done many models on facial emotion recognition using many machine learning, deep learning techniques.

It is great to have a model like this but much more reliable and much more accurate in future by using more advanced techniques.

REFERENCES

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