Face Emotion Recognition

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INTRODUCTION

The Indian education landscape has been undergoing rapid changes for the past 10 years owing to the advancement of web-based learning services, specifically, eLearning platforms. Global E-learning is estimated to witness an 8X over the next 5 years to reach USD 2B in 2021. India is expected to grow with a CAGR of 44% crossing the 10M users mark in 2021. Although the market is growing on a rapid scale, there are major challenges associated with digital learning when compared with brick-and-mortar classrooms. One of many challenges is how to ensure quality learning for students. Digital platforms might overpower physical classrooms in terms of content quality but when it comes to understanding whether students are able to grasp the content in a live class scenario is yet an open-end challenge. In a physical classroom during a lecturing teacher can see the faces and assess the emotion of the class and tune their lecture accordingly, whether he is going fast or slow. He can identify students who need special attention. Digital classrooms are conducted via video telephony software program (exZoom) where it's not possible for medium scale class (25-50) to see all students and access the mood. Because of this drawback, students are not focusing on content due to lack of surveillance. While digital platforms have limitations in terms of physical surveillance but it comes with the power of data and machines which can work for you. It provides data in the form of video, audio, and texts which can be analysed using deep learning algorithms. Deep learning backed system not only solves the surveillance issue, but it also removes the human bias from the system, and all information is no longer in the teacher's brain rather translated in numbers that can be analysed and tracked.

PROBLEM STATEMENT

During online classes students often tends to lose attention, which leads to overall non-productivity. For a teacher, its often important for its students to easily grasp concept taught by them. Teachers have skills to observe their students and improve their way throughout their teaching. But due to online teaching, observing has become tough which has eventually disturbed student teacher balance and teaching methods. So, our aim was to develop a Face-Emotion-Recognition Model which can be used a micro service as well so that teachers can understand students much better and enlighten the way to teach.

INSPECTING DATASET

We use FER2013 dataset for our model making. We download the dataset in folder format from google. Then we split it into train and test. We check the images by printing and found that the image is of low resolution.

On research we get to know that FER2013 is a well-studied dataset and has been used in ICML competitions and several research papers. It is one of the more challenging datasets with human-level accuracy only at 65±5% and the highest performing published works achieving 75.2% test accuracy. The dataset Easily downloadable on kaggle.

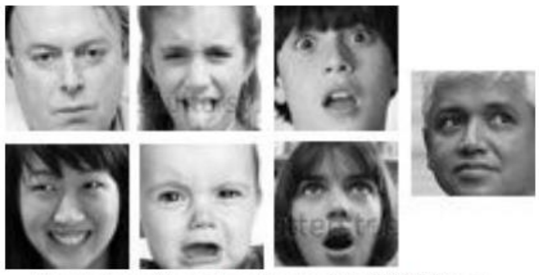


Figure 1: Images from each emotion class in the FER2013 dataset.

Our dataset has 35,887 images, which are normalized to 48x48 pixels in grayscale and classified into seven categories - Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral. However, the FER2013 dataset is not a balanced dataset, as it contains images of 7 facial expressions, with distributions of Angry (4,953), Disgust (547), Fear (5,121), Happy (8,989), Sad (6,077), Surprise (4,002), and Neutral (6,198).

DATA AUGMENTATION

We used ImageDataGenerator first and experimented with rotation of 20, zoom of 0.2 and height and width shifting by 0.1. We found out that models were not performing well after augmentation because the images in dataset are in low resolution so it becomes tough to classify well on its augmented images. After a lot of trial and errors we had to remove augmentation to get better performance of model.

CALLBACK FUNCTION

Callback functions are those functions which are called at the end of every epoch and in this model, we use three callback functions –

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.

Plotting function is defined to plot the accuracy and loss by taking 'history' of the model as input.

__Hyper-parameter used__:

1. epochs = 50

2. batch_size = 64

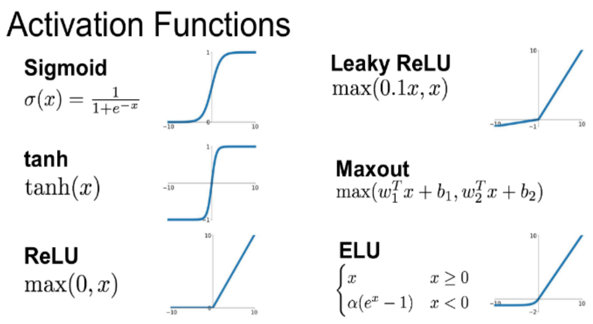
3. learning_rate = 0.0001

4. decay =le-6

TECHNIQUE USED IN MODLES

1. Maximum Pooling (or Max Pooling): like the name states; will take out only the maximum from a pool. This is actually done with the use of filters sliding through the input; and at every stride, the maximum parameter is taken out and the rest is dropped. This actually down-samples the network. Unlike the convolution layer, the pooling layer does not alter the depth of the network, the depth dimension remains unchanged.

2. Activation Function: The activation function is a node that is put at the end of or in between Neural Networks. They help to decide if the neuron would fire or not.



We have different types of activation functions just as the figure above, but for our project my focus will be on Rectified Linear Unit (ReLU). The advantage of using ReLU over other activation functions is that it does not activate all neurons at the same time. From the image for ReLU function above, we'll notice that it converts all negative inputs to zero and the neuron does not get activated. This makes it very computational efficient as few neurons are activated per time.

3. **Batch Normalisation**: Batch normalization, or batchnorm for short, is proposed as a technique to help coordinate the update of multiple layers in the model. It does this scaling the output of the layer, specifically by standardizing the activations of each input variable per mini-batch, such as the activations of a node from the previous layer.

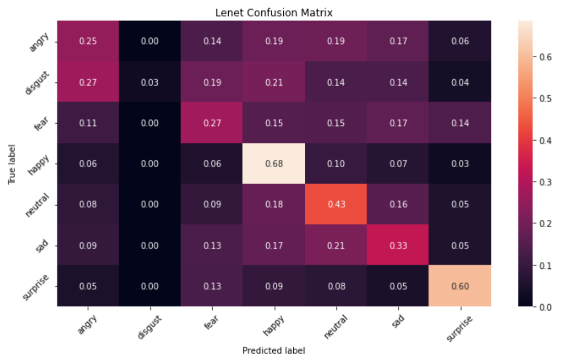
It removes the ill effects of the internal covariate shift. This has the effect of stabilizing and speeding-up the training process of deep neural networks. Normalizing the inputs to the layer has an effect on the training of the model, dramatically reducing the number of epochs required. It can also have a regularizing effect, reducing generalization error much like the use of activation regularization.

4. **Dropout**: The Dropout layer randomly sets input units to 0 with a frequency of rate at each step during training time, which helps **prevent overfitting**. Inputs not set to 0 are scaled up by 1/(1 - rate) such that the sum over all inputs is unchanged. Usually, dropout is placed on the **fully connected layers** only because they are the one with the greater number of parameters and thus, they're likely to excessively co-adapting themselves causing overfitting.

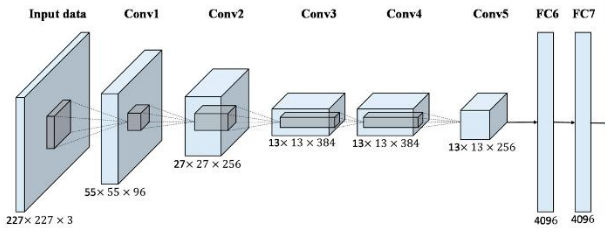
MODELS

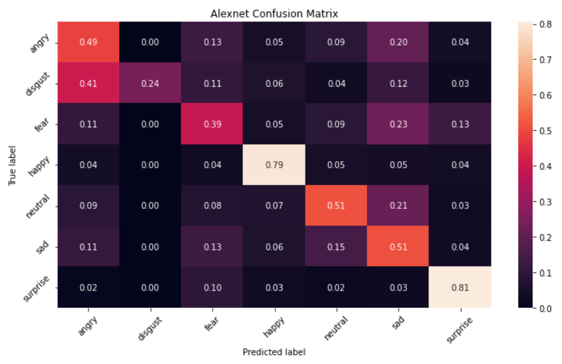
LeNet5

In order to better understand the problem, we decided to first try to tackle this problem from scratch, building a simple CNN using Le-Net 5 and using Relu and max pooling instead of softmax and average pooling. Our model stops training at 15 epoch and the best accuracy was at 6 epoch with training accuracy of 60% and validation accuracy of 44%.



AlexNet : After base line model we train alexnet model, this architecture was publish in 2012 and train roughly on 1.2 million high resolution images into 1000 different classes. After applying this model we got quite good accuracy on both training and validation of 75% and 60% respectively.



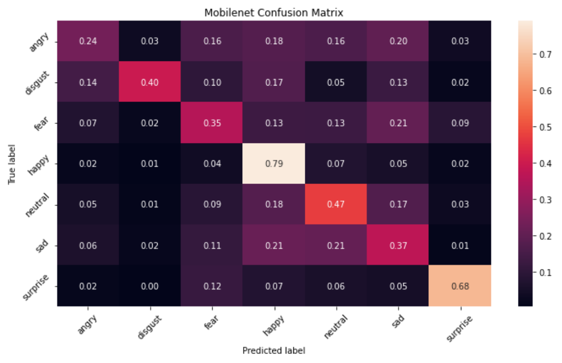


Transfer Learning

Since the FER2013 dataset is quite small and unbalanced, we found that utilizing transfer learning significantly boosted the accuracy of our model. We explored transfer learning, using the Keras library and each of mobilenetv2, VGG16, VGG19 and Resnet as our pre-trained models. To match the input requirements of these new networks which expected RGB images of no smaller than 197x197, we added a convolutional layer with 3 kernels to make the input compatible with models. We achieved fair results on all and the confusion matrix for the validation data for each model is as follows:

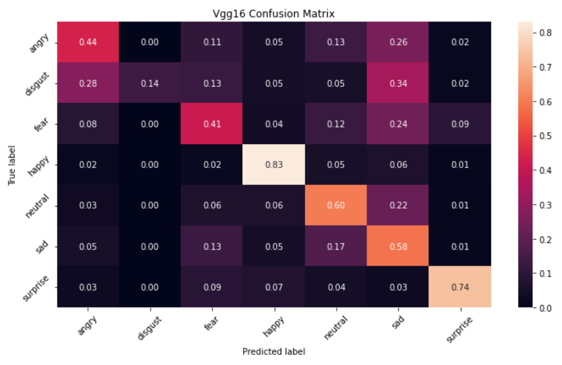
MobileNetv2:

Mobilenet is very lightweight when it comes to deployment and has many more parameters. We added two FC layers of size 128 and 64. After 10 epochs of training with the Adam optimizer, we achieved an accuracy of 51% on the test set.



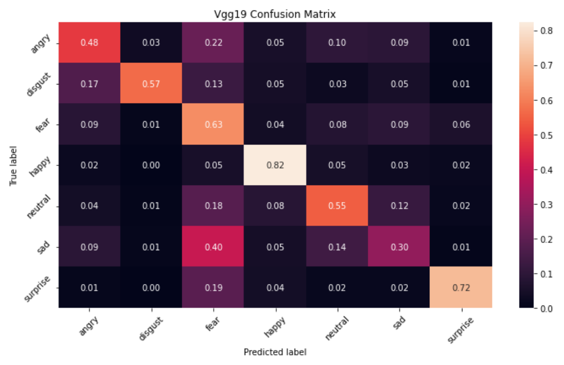
VGG16:

VGG16 is more complex and has many more parameters. We added two FC layers of size 4096 After 7 epochs of training with the Adam optimizer, we achieved an accuracy of 61% on the test set.



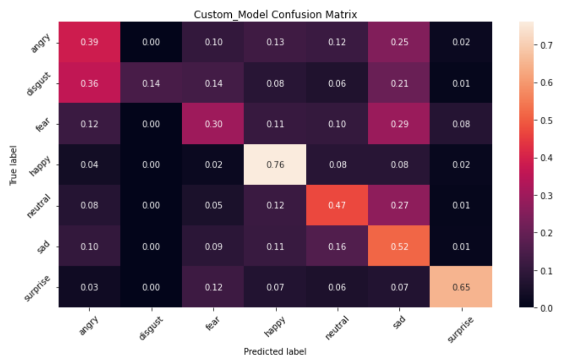
VGG19:

It almost classified all sort of images with fair accuracy however it confusing some sad images as fear images.



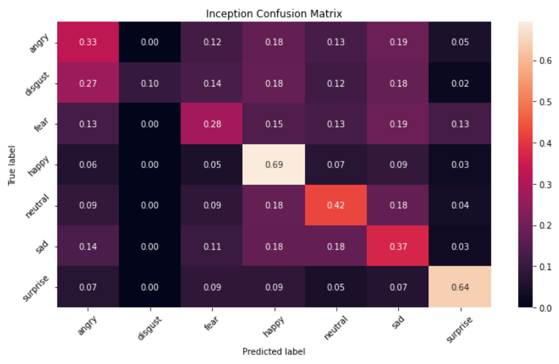
Custom Model:

We also experimented by defining our own CNN architecture with 3 Conv layers followed by 2 dense layers and the final classification layer. It performed quite well on variety of images but it was confusing some disgust faces with angry faces.



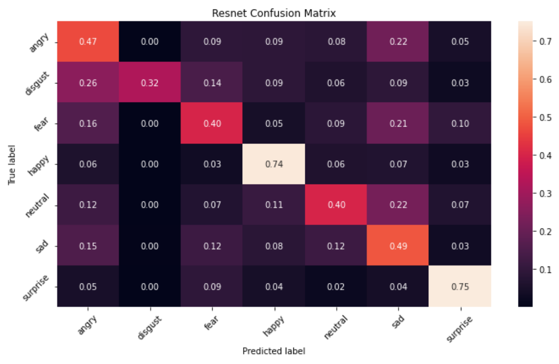
Inception:

It is not an easy task to decide which filter will work best for which case so we wanted to experiment with inception model as well because it uses all many filters in one block. For that we defined a small inception network with only two inception blocks followed by two dense layers and the final classification layer. It was very robust in predicting happy and surprise faces but was confusing disgust faces with fear faces.



Resnet:

After training a lot of complex models, finally we also tested Resnet because of the fact that it is capable of learning identity function which other complex models might not learn easily. So we wanted to see whether training this model makes any difference or not.



Resnet was a little overfitting and was biased towards the training data but it gave around 54% accuracy on test data.

RESULTS:

Below table shows the accuracies our best models achieved on the FER2013 Dataset.

Model	Training Accuracy	Validation Accuracy
Le-net	**60%**	**44%**
Alexnet	**75%**	**59%**
VGG-16	**71%**	**61%**
VGG-19	**75%**	**60%**
Mobilenet	**68%**	**51%**
Custom	**81%**	**53%**
Inception	**56%**	**56%**
ResNet152	**85%**	**54%**

CONCLUSION:

- We experimented with many predefined CNN architectures as well as a custom CNN architecture and after a lot of trial and errors we came up with these models. Highest efficiency in terms of accuracy and execution time is given by vgg16 model so we consider it as our final model.
- Our model is giving an accuracy of around 71% on train data and 61% on the test data and is robust in that it works well even with shear and tilted images even in low light. We tested the model on a local webcam by builting an application and we found that it is able to detect face location and predict the right expression.
- Using this model tutors can percieve the students' emotion during online classes and react accordingly by implementing different technique of teaching.

Reference :

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4. Analytic Vidhya
5. Wikipedia