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Recognitions of Facial Emotions

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Abstract- This paper discusses the application of feature extraction of facial expressions with combination of neural network for the recognition of different facial emotions (happy, sad, angry, fear, surprised, neutral). Facial expression plays a major role in expressing what a person feels. It expresses human perspective or inner feeling & his or her mental situation. A human brain can have lot of emotions but this paper deals with the main 7 emotions. This paper deals with the highly efficient model of the combined models of VGG 16 and . The earlier baseline models used were support vector machine. We have named the combine model as Assemble model. These papers leveraged assemble and transfer learning to achieve the best results.

Keywords – End to End learning, emotion recognize, deep learning, facial emotion recognition.

I. INTRODUCTION

Understanding human emotions is key area of research, as the ability to recognize one's emotions can give one access to a plethora of opportunities and applications, ranging from friendlier human-computer interactions, to better targeted advertising campaigns, and culminating with an improved communication among humans, by improving the emotional intelligence ("EQ") of each of us. While there are multiple ways one can investigate the recognition of human emotions, ranging from facial expressions, and posture of the body, speed and tone of the voice, in this paper we shall focus on only one area of this field - visual recognition of emotions. One of the reasons we chose to focus on the area of facial expressions is because certain facial expressions have universal meaning, and these emotions have been documented for tens and even hundreds of years. "Constants across cultures in the face and emotion" That paper identified the following six key emotions: anger, neutral,fear, happiness, sadness and surprise. These are the same emotions that are being use d by current researchers to identify facial expression in computer vision, or in competitions such as Kaggle's Facial Expression Recognition Challenge, along with the addition of a seventh, neutral emotion, for classification.

Thus, our research is about using deep learning (a VGG- 16 convolution network) to identify these six main human emotions. To us this problem is extremely relevant because of its broad spectrum of applicability in a variety of fields, such as systematic recruiting, while being also able to be integrated with a variety of technologies (i.e. smart glasses, VR, wearables, etc.). Emotions and facial responses can also serve as a new dimension of user information (i.e. imagine Facebook or Google analyzing your emotions and reactions to learn more about the user and serve better recommendations and ads). To achieve our goals, we used a convolution neural network (CNN) to classify these emotions. In particular, we will use some of the current state of the art architecture - VGG-16 , while making some adjustments which include applications of various deep learning techniques, and ensemble and transfer learning . We chose to go with VGG-16 because it won in the past the ImageNet challenge,

achieved near state-of-the-art results in terms of prediction accuracy, and follow a relatively standard CNN architecture. The one datasets we will leverage in our research are the fer2013 We found this datasets to be representative because of its size, unstructured nature of faces (in terms of facial orientation, ethnicity, age, and gender of the subjects) and relatively uniform distribution of the data across the six main human emotions. To evaluate the performance of our models, we will primarily be looking at the accuracy on the training, validation, and test sets. The processes, we will be leveraging other standard statistics such as precision and recall providing further insights on the efficacy of the models. We expect our best model to achieve at least 50% test set valuation.

II. LITERATURE SURVEY

Previous works are focused on eliciting results from uni-modal systems. Machines used to predict emotion by only facial expressions or only vocal sounds .After a while, multimodal systems that use more than one features to predict emotion has more effective and gives more accurate results. So that, the combination of features such as audio-visual expressions, EEG, body gestures have been used since. More than one intelligent machine and neural networks are used to implement the emotion recognition system. Multimodal recognition method has been proven more effective than uni-modal systems by Shiqing et al . Research has demonstrated that deep neural networks can effectively generate discriminative features that approximate the complex non-linear dependencies between features in the original set. These deep generative models have been applied to speech and language processing, as well as emotion recognition tasks .Martin et al. In speech processing, Ngiam et al. proposed and evaluated deep networks to learn audio-visual features from spoken letters. In emotion recognition, Brueckner et al. found that the use of a Restricted Boltzmann Machine (RBM) prior to a two-layer neural network with fine-tuning could significantly improve classification accuracy in the Interspeech automatic likability classification challenge . The work by Stuhlsatz et al. took a different approach for learning acoustic features in speech emotion recognition using Generalized Discriminant Analysis (GerDA) based on Deep Neural Networks (DNNs). In the deep neural approaches, the already used approaches are baseline SVM model which is followed by CNN model with 43.8% efficiency.

III .VGG-16

The input to VGG-16 layer is of fixed size 224 x 224 RGB image. The image is passed through a stack of convolutional (conv.) layers, where the filters were used with a very small receptive field: 3×3 (which is the smallest size to capture the notion of left/right, up/down, center).The convolutional stride is fixed to 1 pixel; the spatial padding of conv. layer input is such that the spatial resolution is preserved after convolution, i.e. the padding is 1-pixel for 3×3 conv. Layers (Figure 1). Spatial pooling is carried out by five max-pooling layers, which follow some of the convolutional layers (not all the conv. layers are followed by max pooling). Max-pooling is performed over a 2×2-pixel window, with stride 2

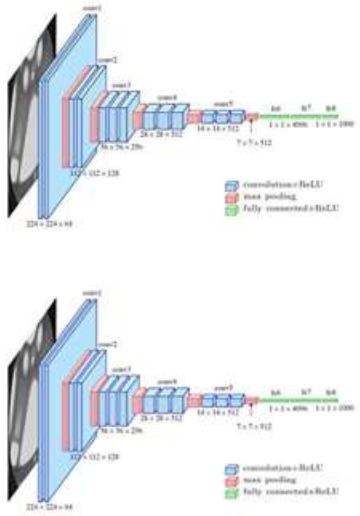


Figure 1: VGG-16 architecture diagram.

The input to our VGG-16 is a 48x48 RGB image. The only preprocessing we do is subtracting the mean RGB from each pixel. The image is passed through a stack of convolution layers ,where we use 3x3 filters.In one of the configurations we also utilize 1 × 1 convolution filters, which can be seen as a linear transformation of the input channels (followed by non-linearity). The convolution stride is fixed to 1 pixel; the spatial padding of convolutional layer input is such that the

spatial resolution is preserved after convolution(i.e.the padding is 1pixelfor 3 × 3 conv. layers). Spatial pooling is carried out by five max-pooling layers, which follow some of the convolutional layers (not all the convolutional layers are followed by max-pooling). Max-pooling is performed over a 2 × 2-pixel window, with stride2.

A stack of convolutional layers is followed by three Fully Connected (FC) layers: the first two have 4096 channels each, the third performs 7-way ILSVRC classification and thus contains seven channels (one for each class). The final layer is the so ft max layer. The configuration of the fully connected layers is the same in all networks. All hidden layers are equipped with the rectification (ReLU) non linearity.

To conclude, VGG-16 consists of 16 weight layers that include13 convolutional layers with filter size of 3x3 and 3 fully connected layers. The stride and padding of all convolutional layers are fixed to 1 pixel. All convolutional layers are divided into 5 groups and each group is followed by a max-pooling layer (Figure 1). Max-pooling is carried out over a 2x2 window with stride 2. The number of filters of convolutional layer group starts from 64in the first group and then increases by a factor of 2 after each max-pooling layer, until it reaches 512. We leveraged the keras implementation of VGG-16

IV. RESULTS

The precision shows us the positive predictive value, and recall captures the sensitivity or true positive rate of the models. To compute the overall precision and recall, we use micro-averages to combine the results across all six emotions. To further understand and assess our models, we examined the metrics for each emotion as well as the confusion matrix.

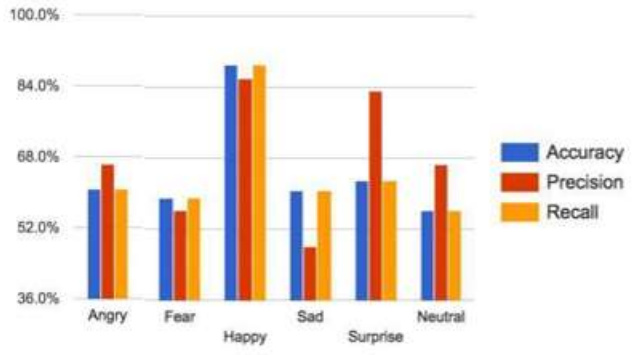
The overall accuracies along with precision and recall on the KDEF dataset are greater than those on the Kaggle dataset. while VGG- 16 achieved an accuracy of 60%. (Table2).
The ranking of the four models is the same. We conjecture that this may be a result of the structure and uniformity of the fer2013 dataset in terms of the subjects' postures and number of examples for each subject and each emotion.The images in the fer2013 data set are also of higher quality. Aside from better image resolution, there were examples in the fer2013 dataset where there was, for example, text overlay in the background of the image.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where TP= True Positive, TN= True Negative
FP= False Positive, FN= False Negative.

Applying further improved the results. After training the VGG-16 models on the fer2013 dataset, we fixed the layer weights aside from the last few layers of these models and retrained on the dataset. This led to a 2.5% accuracy improvement in our ensemble model which was our best performing model (Table 3). Precision and recall were similarly improved. This shows that the model was able to leverage the learnings from the faces of the fer2013 dataset which contained a wider and more abundant distribution of data .
The diagram below shows (accuracy, precision, and recall) with transfer learning from the model.

The minimum accuracy, precision, and recall are 56.1% (neutral), 48.2% (sad) . Sadness and neutrality, as we further discuss later on, possess similar facial features as each other and a couple other emotions. We also note that we performed the best on happiness, which may be due to having the most data coverage for this emotion.



Happy Surprised Neutral Angry Fear

Happy	99.979	0.007	0	0	0.007	0
Surprised	0	99.378	0	0.331	0.03	0.258
Neutral	0.363	23.765	75.48	0.004	0.004	0.378
Angry	0.001	0.008	0	99.99	0	0
Fear	0	0.256	0	0.333	99.375	0.005
Sad	0.006	0.001	0.001	0.001	1.224	98.763

Figure 3 shows the confusion matrix for our best performing model on the fer2013 dataset. The correlations between actual and predicted emotion hold for the other three models we experimented with. The matrix reveals that anger, disgust, fear, and neutrality tend to get miss categorized with sadness. Conversely, sadness tends to be miss categorized with the same set of emotions. Looking at the raw images, we can qualitatively see that the facial expressions for sadness have commonalities with that for those emotions, especially the aspects of the mouth area (aside from anger).Since we did not add additional features aside from the processed image pixels; it isn't surprising that these emotions are confused with one another. Lastly, surprise is confused with both fear and happiness.

V. FUTURE WORK SCOPE

We are working towards a machine with emotions. A machine or a system, which can think like humans, can feel warmness of heart; can judge on events, prioritized between choices and with many more emotional epithets. To make the dream reality first we need the machine or system to understand human emotions, ape the emotion and master it. We just started to do that. Though there is some real example exists these days. Some features and services are getting popularity like Microsoft Cognitive Services but still there is a lot works required in the terms of efficiency, accuracy and usability. Therefore, in future Emotion Recognition is an area requires a great intentness

VI. CONCLUSION

We explored the VGG-16 architecture for recognizing facial emotions using deep learning. The results demonstrated that we were able to achieve acceptable results from fer2013 dataset. We further improved these models by suitable datasets.

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