AI Emotion Recognition

Project Report

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On our honor as UNT students, We have neither given nor received unauthorized assistance on this work.

Abstract

Research has indicated that human emotion can be detected via facial expressions and speech, and identifying these emotions may be a quality innate to most humans. Distinctly classifying these emotions can be difficult, and prime human emotions have been even more difficult to identify. Machine learning models allow us to not only solve prediction problems, but see how different models solve these problems in a specific domain. By identifying underlying patterns and using dimensionality reduction via machine learning, we may be able to better understand the distinctions and similarities between human emotions and how we perceive them in others. We hypothesize that we may be able to identify a set of prime emotions that are recognizable by machine learning models. This will be accomplished by gathering large datasets of labeled facial expressions. A model that can accurately detect human emotions in individuals will help social services such as psychiatry, rehabilitation and counselling, by helping bridge any gaps in empathy between patient and caregiver.

Introduction

Machines and humans differ in how they perceive humans. Humans can easily identify emotions in others from a fairly early age. However, quantifying these emotions is more difficult, and methods and classifications of recognizable human emotions are debated.

We will show that our method of recognizing emotions from images of faces will improve the F1-measure of the classifier by 33% compared to choosing the most frequent class when applied to images of unseen people's faces.

We hope that with further development our system may prove useful to caregivers, psychiatrists, therapists, and others who are in positions where identifying patient emotions are critical. This system can be used as a tool for objective identification of human emotion.

Related Work

There have been previous attempts to solve this problem, and these are the ones that we have used to inform our model.

Hidden Markov model-based speech emotion recognition

B. Schuller, G. Rigoll and M. Lang, "Hidden Markov model-based speech emotion recognition," 2003 IEEE International Conference on Acoustics, Speech, and Signal Processing, 2003. Proceedings. (ICASSP '03)., Hong Kong, 2003, pp. II-1

Facial Emotion Recognition Using Machine Learning

Raut, Nitisha, "Facial Emotion Recognition Using Machine Learning" (2018). Master's Projects. 632.

DOI: https://doi.org/10.31979/etd.w5fs-s8wd

https://scholarworks.sjsu.edu/etd_projects/632

Data

Finding readily datasets for this issue has proven difficult. Ultimately we settled on the Facial Expression Recognition 2013 (FER-2013) Dataset. This was a dataset that we were able to download from kaggle, without the need for signing up or requesting access:

https://www.kaggle.com/c/challenges-in-representation-learning-facial-expression-recognition-challenge/data

The data consists of 48x48 pixel grayscale images of faces. The faces were labeled with an emotion from seven categories.

0=Angry, 1=Disgust, 2=Fear, 3=Happy, 4=Sad, 5=Surprise, 6=Neutral

The data set is also split in to training, validation and testing sets:

Training Instances: 28709

Validation Instances: 3589

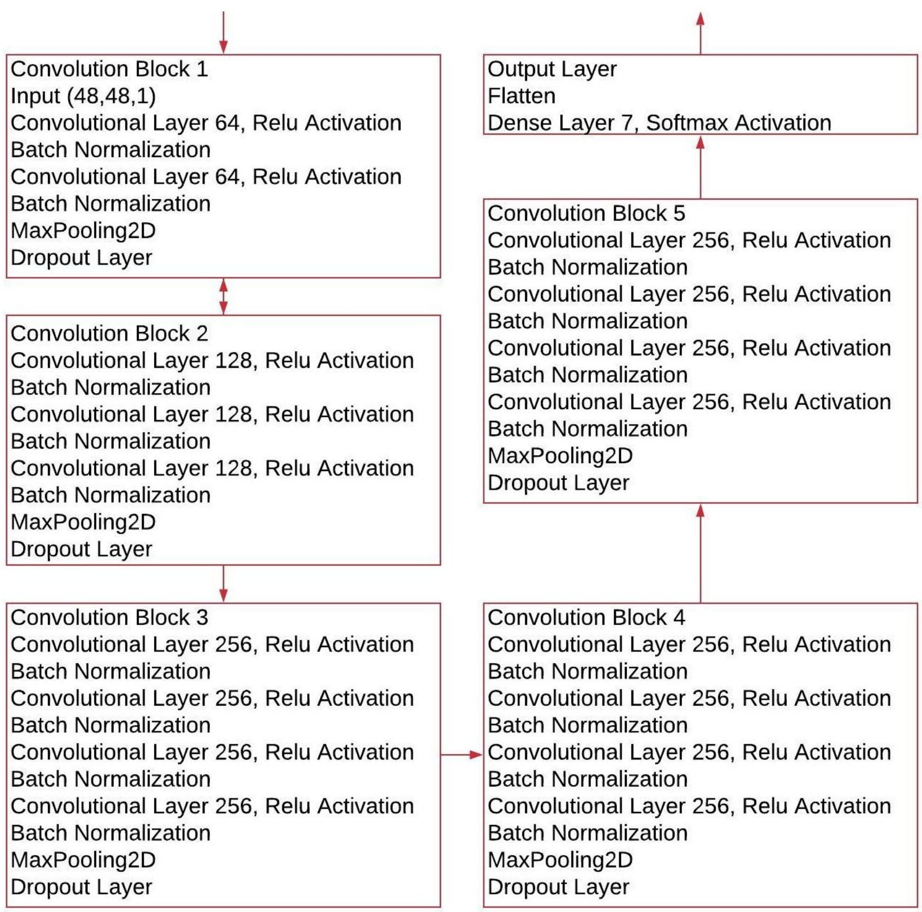
Test Instances: 3589

Methodology

We have used deep neural networks to identify facial patterns in order to identify the specific emotions. Specifically we have employed Keras Convolutional Neural Networks. Convolutional networks, using downsampling, are very useful for image recognition due to their ability in identifying patterns in an image space. This has also proven helpful in identifying human emotion.

Model Architecture

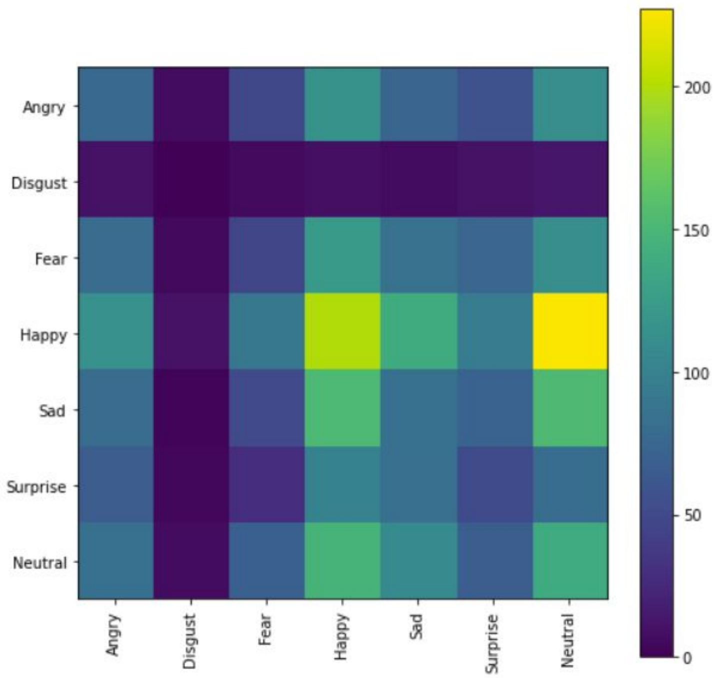
Our architecture consists of 5 convolution blocks and were in this configuration:



Results

Our results seemed promising, but indicate a lack of samples for the disgust classification.

Happy:	8989
Neutral:	6198
Sad:	6077
Fear:	5121
Angry:	4953
Surprise:	4002
Disgust:	547



As you can see by our heat map, the model had the hardest time with classifying Disgust in the test set. We could do better with including more datasets.

Finally we have included a video of the model performing classification in real time using our webcam:

https://www.youtube.com/watch?v=06kBlptfEz4&feature=youtu.be