Facial Expression Recognition for Cloud Robotics

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ABSTRACT

As social robots become widespread, it will be essential that they can classify the emotions of humans around them, in order to interact in a meaningful and helpful way. But limited hardware means they may have to offload video data to the cloud, reducing the resolution of the content. This work focusses on evaluating the fitness of neural network models for cloud computing, specifically the effect of changing spatial and temporal resolution on the classification of emotion in video. I build different models to asses each models performance when given lower resolution video. The results show that by applying a CNN-LSTM model to a 8-class problem, we can achieve 81% accuracy on high resolution video, and maintain a minimum 67% accuracy across a range of resolutions. To the best of my knowledge this is the first work that investigates the effect of changing both spatial and temporal resolution on video-based sentiment classification.

KEYWORDS

Affective computing, robotics, cloud computing, emotions, arousal, valence, resolution.

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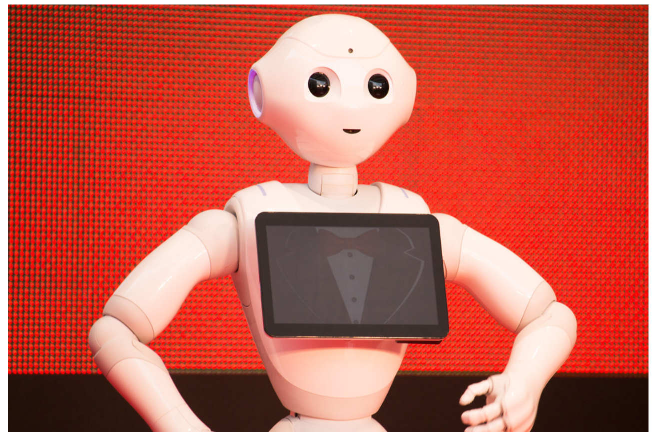

Figure 1: Pepper by SoftBank Robotics, an example of a social robotic platform which has been trialled in care homes in the UK. Photograph by Dick Thomas, via creative commons (source).

1 INTRODUCTION

Social robots are becoming increasingly widespread, with uses in a wide range of locations, providing help in hospitals [5], care homes [7] and schools [24]. These robots are frequently required to interact meaningfully with humans, and in order to do so it is essential that they are able to classify emotions to react accordingly. However, many social robotic platforms lack the computational hardware required to perform classification [3]. Hence, it will likely become necessary to move to a cloud robotic framework, where sensing data is offloaded to the cloud and processed there. Unreliable network conditions mean we must be prepared for video data to enter the cloud at reduced spatial and temporal resolutions.

In past years, neural networks have become ubiquitous for classifying emotion, due to their ability to learn pattern humans would be unable to program in. However they can suffer from not being generalizable, especially if a network is trained in one domain, then deployed in another. For example, a network trained on high resolution data would be less effective at classifying low resolution data.

For classifying images, there is a large volume of work looking at using convolutional neural networks (CNNs). When applied to an image, a CNN convolves a filter with the pixel data, generating meaningful features. CNNs have found widespread use across various domains, including facial recognition [19] and object detection and classification [32]. Several architectures have been proposed offering impressive ability to learn features from video using purposes, for example the VGG16 network [30] and the ResNet50 network [12], both of which were able to achieve winning results in the ImageNet object detection and classification challenge [28].

For classifying videos, it is often vital to take temporal data into account, and as a result Recurrent Neural Networks (RNNs) [27] are a good choice. RNNs have some internal state, or memory, which they use to process sequences, learning patterns that may vary over time. A very popular architecture is Long Short Term Memory [13] (LSTM), which make use of gates to control the flow into and out of cells in the architecture. LSTMs have found wide usage, across speech recognition [11], market prediction [29] and handwriting recognition [10].

In this work we create a couple of classifiers which are tested on video at a variety of resolutions and frame-rates, in order to deduce which classifiers may be useful for cloud robotics. The classifiers

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are tested on a 7-class video dataset, and our results show that we can achieve an accuracy of X on

The rest of the paper is structured as follows: Section 2 gives an overview of previous work on similar problems, Section 3 gives detail about the methodology employed in the study. Then, Section 4 discusses the results before Section 5 goes over future research directions. Finally, Section 6 concludes the paper with an overview of the findings.

2 RELATED WORK

In this section I give an overview of facial expression recognition techniques, first for images, and then for videos, followed by a section on classifying data at reduced resolutions.

2.1 Facial Expression Recognition in Images

Facial expressions have allowed humans to communicate their emotions amongst each other for years. There has been a large volume of research into the mechanisms which allow this non-verbal communication to happen. An early work by P. Ekman and W.V. Friesen introduced the Facial Action Coding System (FACS) [8], which described a list of facial action units - regions which change as a person changes their expression. The work further describes how a given facial expression could be described as a combination of action units. Following this work, P. Ekman et al. detailed how a mapping can be made between the facial action units and a person's emotions [6]. I will now detail the work that has been put into using machines to detect emotions from photos, splitting the research into those that make use of deep networks, and those before deep networks became widespread.

Before the use of deep networks, there were two main approaches to sentiment classification for images - rule-based methods, and appearance based methods. First, the rule-based methods were centred around detecting facial action units individually, and then piecing together the results from the facial action unit recognizers to derive an overall emotion, for example in Y. Tian et al.'s work [33]. These techniques suffered as recognizing an individual action unit is not an easy task. In the alternative approach, appearance based methods, some features are extracted from the overall face, and then those features are passed through a machine learning classifier. For example, M.S. Bartlett et al. found that they could achieve good results by extracting features using Gabor filters, followed by a Support Vector Machine (SVM) [2]. Additionally, J. Whitehall and C. Omlin showed that comparable results could be obtained in significantly quicker time by instead using Haar wavelets to obtain features before passing through a SVM [36].

In previous techniques, processing of emotions had been split into learning features, selecting features and then using a classifier to learn the patterns. The downside of taking that approach is that the first layers do not get feedback from the latter layers. Deep learning aims to solve that, by integrating the feature finding, selection and classification into one deep network that can be trained at once. One of the early papers making use of this technique was by P. Liu et al. [22], who suggested using a Boosted Deep Belief Network. This network consisted of several deep networks learning features, and some of these networks get boosted based on their performance. Finally, in [20], Liu et al. introduced CNNs to the problem, with their CNN Ensemble network. The network consisted of three different convolutional networks, which proved to achieve better results than a single CNN.

2.2 Facial Expression Recognition in Videos

When classifying emotion in videos, there is additional information that can be extracted by accounting for the way the face changes over time. There are several papers which attempt to do this, which I will now go over, beginning with aggregation techniques. Aggregation techniques classify each frame within a video, and then combine the results with some sort of aggregator. In [14] and [15], S. Kahou et al. split the video into 10 sections, and within each section aggregate the frame predictions with an average. They go on to use a SVM to classify using all 10 aggregate predictions. An alternative method was introduced in [21] where M. Liu et al. showed that features from individual frames could be mapped to linear subspaces, covariance matrices or Gaussian distributions, allowing these to be passed to a support vector machine.

An alternative approach focussed on attempts to classify the level of emotional intensity present in an individual frame - the idea being that you could derive the emotion of a video base on the strongest emotions present. In [37] X. Zhao et al. propose a network which minimizes the differences between an emotion at low intensity and the same emotion at high intensity, as a way to get better classification of low intensity emotion. The downside of their technique was that it required a training set consisting of pairs of the same emotions at different intensities. To address this, in [4] J. Chen et al. used unsupervised clustering and a semisupervised SVM to detect peak and neutral frames in a large dataset.

Finally, deep spatio-temporal networks were introduced which use sequences of frames as inputs to the networks, in the hopes that we can learn more information from the temporal dynamics of the images. C3Ds [35] are the natural generalization of a CNN to 3 dimensions - instead of convolving an image with a 2D kernel, we convolve a sequence of frames with a 3D kernel. These 3D techniques have been bought to video emotion recognition, for example by X. Ouyang in [25]. An alternative approach was taken in [17] where D. Kim et al. tracked facial landmarks to generate trajectories which were used as features. Finally, a common approach is to use a CNN to learn spatial features of an image followed by a LSTM to learn the temporal features of the overall video, as in [16].

2.3 Reduced resolution classification

There have been a couple of studies looking at how to cope when the face that needs to be classified is at a low resolution. Firstly, Y. Tian [34] looked at how low spatial resolution would affect three steps in a facial expression analysis pipeline: face acquisition, facial data extraction and finally expression recognition. Also, R. Khan et al. produced a framework for expression recognition on low-resolution images [**?**], by suggesting a new set of features which work on low resolution images - called pyramid of local binary pattern. Finally, T. Vo et al. proposed the pyramid with super resolution architecture [**?**], which made use of super resolution networks in order to scale up low resolution images with minimal artefacts.

3 METHODOLOGY

In this section, the goal is to build to a classifier which we can use to test video at multiple spatial and temporal resolutions. We first introduce the datasets used in the work, then discuss the image classifiers produced, before finally talking about the techniques used to classify the videos.

3.1 Datasets

For learning facial expressions of images I used the FER+ dataset [1] from E. Barsoum et al., a large collection of images first as part of the FER-2013 dataset [9]. The FER-2013 dataset consists of 36,685 48x48 greyscale images obtained by searching for different emotions on Google Images. The dataset is split into 7 categories - angry, sad, disgust, fear, happy, surprise and neutral. FER+ uses the same collection of images as in FER-2013, but updated the labels to be more accurate by crowd-sourcing the labelling and getting 10 taggers to label each image. In this work, we use majority voting to decide the ground truth of the images, discarding those for which there is no majority.

To learn facial expressions in videos, I used the RAVDESS [23] dataset by SR. Livingstone and FA. Russo. The dataset consists of 24 professional actors speaking two different statements while expressing one of eight emotions. The emotions include calm, happy, sad, angry, fearful, surprise, disgust and neutral. The data is provided at 720p, 30 fps with a blank background, in laboratory settings.

To pre-process the video data, we crop the images to a box around the face. In order to detect the bounding box around the face, we make use of Haar cascades. The purpose of this study is not to focus on how to detect faces at a reduced resolution as there is sufficient work already on that topic [38], [34].

3.2 Training Image Recognition

I used a ResNet50 CNN architecture which is a 50 layer versions in the family of Residual Networks, designed by K. He et al. [?]. They were designed to tackle image recognition tasks, and were significantly deeper than previously introduced architectures, which allowed them to gain accuracy in several recognition tasks. Further, despite the increase in depth, they managed to make the networks relatively easy to optimize.

Instead of training the network beginning with random parameters, I made use of transfer learning - where you use network weights obtained from a different task. This helps to bootstrap the network, giving it a good place to start learning the task you want. We use two different base models, which are publicly available - the first is trained on ImageNet [28], a massive dataset of over a million images, sorted into various nouns. Also, we use weights trained on the VGG Face dataset [26], which consists of 9,131 images of different people's faces. To train, I take the top layers off the pre-trained network, and then add two dense layers to perform the classification on my task. I freeze the original base of the network and train just the new top of the network. After this is complete, I unfreeze the network and train the entirety of the network.

To train the network we use stochastic gradient descent, and in order to obtain good hyperparameters we use Bayesian optimization [31]. Bayesian optimization represents the problem as a Guassian process, which maps hyperparameters to the optimization criteria. By doing this, it can focus the hyperparameter search on those regions which are most likely to lead to good results.

3.3 Training Video Recognition

To classify video, I decided to make use of the best network I previously used for classifying images with the logic that the patterns learnt there would be applicable in the video domain too. In order to extend the network that was designed for single images to video, with several frames, I made use of 3 different techniques. The first two are quite simplistic - I classify each frame of the video before then taking some aggregate of those results. For the first technique, this aggregate is a mean of all the classification scores. The second technique is where I take the max class for each frame, and then take the mode of these classifications.

The third technique I used was a LSTM network, appended to the output of the ResNet, to form a CNN-LSTM architecture. I used a LSTM with 1024 units, which means the LSTM outputs 1024 different features. I follwed the LSTM with two dense layers for the final classifcation. The model was trained using the Adam optimizer [18], which promises to be well suited for optimization problems with a large number of parameters and data. As input to the network, I use 30 frames sequences from the video, and if the video was shorter than 40 frames I repeat frames until we get 30.

To preprocess the video, I created copies of the video at 3 different resolution and 3 different frame rates, for a total of 9 different clips for each input. The resolutions and frame rates were chosen such that they give a wide range of what may be possible over the internet. For resolutions, we had 720p (1280x720 px), 360p (480x360 px) and 144p (256x144 px), and for frame rates we had 30 fps, 15 fps and 5 fps. 720 fps at 30 fps is feasible with a fast internet connection, and low proximity to the server, and 144p at 5 fps would happen with a poor internet connection and/or large distance from a server.

4 EVALUATION

In this section I walk through the results of the experiments, starting with the image recognition task and then moving on to the video recognition tasks.

4.1 Image Recognition

In our image recognition task, I trained a ResNet50 network on the 7-class FER+ dataset, using transfer learning, with two different starting points. One network was pre-trained on the ImageNet dataset, and one on the VGG Face dataset. The recall and F1 score for each class, along with the overall accuracy are plotted in Table 1. The table clearly demonstrates that the VGG pre-train outperforms ImageNet in each class, which is likely due to the fact that VGG model had been trained to recognize specific facial features, whereas ImageNet model is trained on a much wider set of objects so is less dedicated to recognizing faces.

One area where both models underperform is in classifying disgust. This is largely due to the fact that the FER+ dataset is quite unbalanced, with very few disgust expressions within. Furthermore, the line between disgust and anger is quite small, meaning that 47% of the disgust images end up being labelled as anger, as can be seen in the confusion matrix in Figure 2.

Table 1: Classification results on the test set of the FER+ dataset.

model	anger		disgust		fear		happiness		neutral		sadness		surprise		Overall
	Recall	F1	Recall	F1	Recall	F1	Recall	F1	Recall	F1	Recall	F1	Recall	F1	Accuracy
RN50 on VGG	**0.86**	**0.85**	**0.33**	**0.45**	**0.49**	**0.58**	**0.95**	**0.94**	**0.65**	**0.71**	**0.85**	**0.86**	**0.91**	**0.88**	**0.86**
RN50 on ImageNet	0.63	0.67	0	0	0.21	0.34	0.89	0.88	0.44	0.53	0.81	0.8	0.9	0.82	0.78

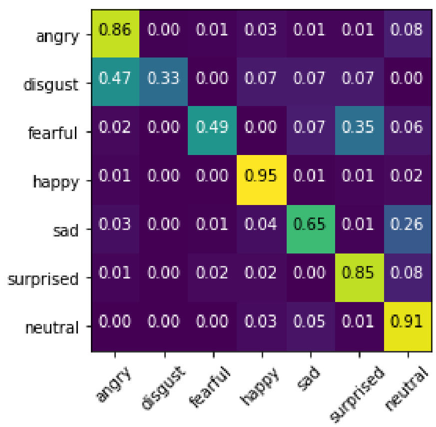

Figure 2: Confusion matrix ResNet50 pre-trained on VGG Face Dataset.

4.2 Video Recognition

In the video recognition task, I tested three main ways in which we could use the ResNet50 model in order to predict the sentiment in videos. The dataset I used was the 8-class RAVDESS emotional video dataset.

5 FUTURE WORK

6 CONCLUSION

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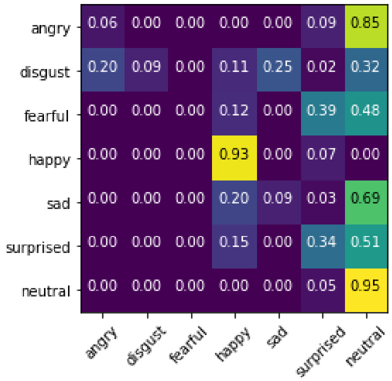
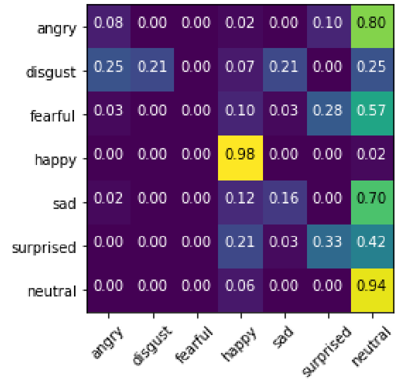
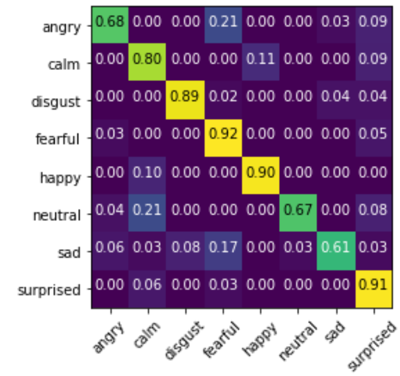
Figure 3: Confusion matrices for video classification on the RAVDESS dataset, based on the best results for any fps/resolution.



(a) Mean Classification



(b) Mode Classification



(c) LSTM Classification

(a) Classification accuracy on the RAVDESS test set, using mean.

	Framerate (fps)		
Resolution (px)	30	15	5
1280x720	0.26	0.31	0.30
640x360	**0.33**	0.30	0.28
256x144	**0.33**	0.29	0.31

(c) Classification accuracy on the RAVDESS test set, using LSTM.

	Framerate (fps)		
Resolution (px)	30	15	5
1280x720	0.67	**0.81**	0.77
640x360	0.77	0.77	0.75
256x144	0.80	**0.81**	0.76

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