

Group-level Emotion Recognition using Transfer Learning from Face Identification

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ABSTRACT

In this paper, we describe our algorithmic approach, which was used for submissions in the fifth Emotion Recognition in the Wild (EmotiW 2017) group-level emotion recognition sub-challenge. We extracted feature vectors of detected faces using the Convolutional Neural Network trained for face identification task, rather than traditional pre-training on emotion recognition problems. In the final pipeline an ensemble of Random Forest classifiers was learned to predict emotion score using available training set. In case when the faces have not been detected, one member of our ensemble extracts features from the whole image. During our experimental study, the proposed approach showed the lowest error rate when compared to other explored techniques. In particular, we achieved 75.4% accuracy on the validation data, which is 20% higher than the handcrafted feature-based baseline. The source code using Keras framework is to be made publicly available.

CCS CONCEPTS

• **Computing methodologies** → **Image representation;**
Supervised learning by classification; **Supervised learning;**
Neural networks;

KEYWORDS

EmotiW 2017, Transfer Learning, Facial Expression Analysis, Group-level Emotion Recognition, Emotion Recognition in the Wild, Convolutional Neural Network

1 INTRODUCTION

Image-based analysis of human activity and social behavior has attracted significant attention in the computer vision community during the past decade, since it can potentially produce a lot of interesting and useful applications, such as digital security surveillance, human computer interaction, street analytics, etc. A lot of above mentioned applications require to analyze emotions depending on particular use-cases. The main direction for this task is to identify faces in the photos and perform further detection of particular emotion [1].

There are various well-known methods for facial expression recognition, which contain different types of feature descriptors, such as facial Action Units (AUs) [2], geometric landmarks [3] or the Convolutional Neural Network (CNN) [4], [5]. However, relatively little research has examined ‘Group’ emotion in images [6], [7]. This task can be helpful for crowd analytics, security and social analysis. During EmotiW 2016 challenge, several CNN-based approaches have been proposed to deal with inferring happiness intensity of a group of people in images [8], [9], [10].

This year, the challenge has advanced to extract group emotion from “in the wild” photos made in various environments from a broader valence range [11] including positive, neutral and negative emotions. In this work, we study various techniques for detection, feature extraction, emotion classification as well as end-to-end methods based on deep CNNs, which have proven themselves effectively in complicated computer vision tasks such as object detection, human pose estimation and image segmentation. We propose an ensemble of classifiers, which includes: 1) the transfer learning techniques to recognize facial emotion from rather different face identification task [12], [13], 2) processing of facial landmarks [3], [9]; and 3) extraction of the CNN features from the whole photo.

The rest of the paper is organized as follows. Section 2 describes the proposed solution. In Section 3 the experimental results using the validation subset of this sub-challenge are discussed. Finally, in Section 4 we give the short summary and concluding remarks.

2 MATERIALS AND METHODS

2.1 Data overview

The main objective of EmotiW 2017 Group-level sub-challenge consists in accurate classification of a groups perceived emotion given an image, which represents natural scene with a group of people. The task is to assign each of the images one of 3 labels: Positive, Neutral or Negative.

The images in this sub-challenge are from the Group Affect Database 2.0 [11]. Statistics of the labels distribution over the train / validation subsets can be found in Table 1. Example of the training image showed in Fig. 1.

Table 1: EmotiW 2017 [2] data overview

Subset	# frames	#Positive	#Negative	#Neutral
Train	3630	1272	1159	1199
Validation	2065	773	564	728
Test	772			

**Figure 1: Example of validation image with neutral label.**

One of the distinctive characteristic of this particular data is that images can be from positive social events such as convocations, marriages, party or neutral event such as meetings or negative events such as funeral, protests etc. The challenging property of the data is that images include faces of different scales, with illumination changes, object occlusions, various ages and non-trivially global context.

2.2 Face Detection

First block of our solution is a face detector. In particular, we need to find all faces on the group photo for the further facial expression analysis. At this stage, we decide to find faces with the traditional algorithms, namely, the Viola-Jones cascade classifiers based on the Haar features [14] from OpenCV library, and linear classifiers over an image pyramid in sliding window manner based on the Histogram of Oriented Gradients (HOG) descriptor [15] from DLIB library. In our experiments, we have found that on the most accurate face detector for EmotiW training and validation data is the DLIB frontal detector.

We tried recently open-sourced technique called TinyFace Detector [16] which is the deep CNN trained on WIDER Face dataset. In particular, we chose ResNet-101 [17] based Tiny Face Detector and obtained much more correct facial regions when compared to the classical techniques. However, in our experimental study emotions on such tiny faces were poorly recognized. Hence, in the final pipeline we decided to use

conventional approach. Namely, we extracted the faces using the detector from DLIB. However, sometimes it was not able to detect any of the faces from the training/validation/test subsets. In order to obtain sufficient amount of training data, we decided to use both DLIB and OpenCV face detection in sequential manner: first we run frontal face detector from DLIB library and if it does not return any face detections then we try to run OpenCV Haar cascades. This particular choice was done by practical observation that Haar cascade tends to return a lot of false positives, which can negatively affect the whole solution.

2.3 Deep face feature extractor

One of the most important parts of the presented algorithm is the deep face feature extractor. Nowadays the feature extraction is typically implemented with the transfer learning methods [18], [19]. The CNN is trained with an external large dataset, e.g., one of the previous EmotiW datasets [5] or FER2013 [20]. The outputs of the CNN's last layer for the input image and each reference image are used as their feature vectors. After that, conventional machine learning techniques, e.g., support vector machines or random forests are applied for these features to recognize facial expressions.

However, in this paper we propose to use CNN trained to identify faces rather than recognize emotions. In fact, the face recognition task is much better studied when compared to emotion recognition. As a result, the volume of the external face identification datasets available to train a deep CNN is much higher. Since we analyse human faces, we assumed that the features for face recognition and facial expression analysis can be rather similar.

As a result, we decided to extract facial features using the VGGFace neural network [12], which was pre-trained for face recognition using the large VGG face dataset (2.6M images of 2622 identities). Each of the facial images was resized to 224x224 resolution, fed to the input of the VGGFace CNN. The 512 outputs at "avgpool" and 4096 outputs at "fc7" layers are stored in the corresponding feature vectors. Experimentally, we have observed that this CNN sometimes performs better if we performed channel permutation (RGB to BGR). It was decided to include this trick into the final pipeline, so we get two "avgpool" and two "fc7" vectors (in total, 4 feature sets) per each face.

After extracting CNN features for each detected face, we computed the final feature vector of the whole image as the median of corresponding features of individual frames. We also tested the more traditional average pooling technique with computation of the mean feature vector, but it degrades the accuracy on 1-2% in all our experiments.

2.4 Face landmarks estimation

The next building block of our solution is the facial landmarks estimation. Facial landmarks are found with the help of DLIB implementation of the method described in the paper [21], which was trained on the iBUG 300-W face landmark dataset. As an example of feature engineering, we have found that beyond

features extracted by CNN, it can be helpful to use distances between facial landmarks.

In particular, we computed all unique pairwise distances between extracted 68 facial landmarks and normalized these distances to prevent the dependence on the facial region size. To do this, we simply divide all distances by the maximum of the computed distances between founded landmarks. During experiments, we also tried to normalize landmarks distances by mean distance value, however, such normalization caused small accuracy degradation.

2.5 Proposed approach

By using described features we learned the final classifier which predicts the group image emotion label. In our work we implemented most popular classifiers including Logistic Regression, Support Vector Regression, Gradient Boosting Trees and Random Forest. It was experimentally identified that the best choice of the trainable classifier is Random Forest, which performed the best on the validation data.

The final pipeline is shown in Fig. 2. It was constructed as an ensemble of four Random Forest classifiers trained on VGGFace “avgpool” (before the first fully connected layer) and “fc7” features for RGB and BGR representation of the face. An additional Random Forest classifier was trained on the normalized landmark distances. To tackle the problem of images where our detectors failed to extract any face, we fine-tuned a VGG16 model [22] pre-trained on ImageNet dataset [23] to perform the end-to-end classification for the full image. This classifier is also included in the ensemble. To obtain the final decision, the outputs of individual classifiers are weighted based on their accuracy estimated on the validation data.

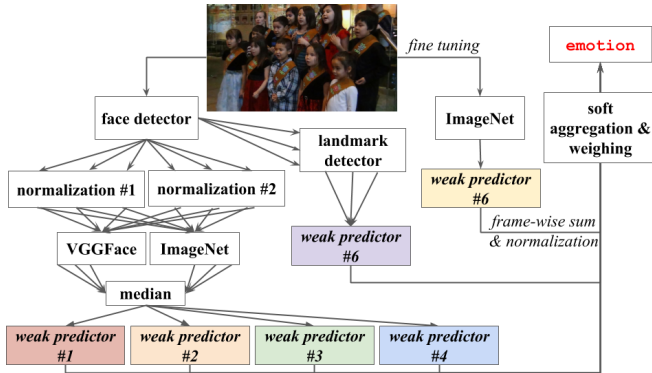


Figure 2: Proposed approach

3 RESULTS AND DISCUSSION

Classification accuracy is used as the metric in the challenge. All deep CNNs in this experiment were implemented using Keras library on top of the Tensorflow framework. In the experimental study the proposed approach (Fig. 2) was compared with the baseline support vector regression model for the CENTRIST scene descriptor [6]. For our network, we used Adagrad optimizer

with learning rate of 1e-4, batch size of 40, aggressive data augmentation and trained this network for 30 epochs.

In addition, we consider traditional approach with the end-to-end learning by fine-tuning several modern CNNs (VGG-16 and VGG-19 [22], VGGFace [12], ResNet-50 [17] and Xception [24]) using the detected faces. In this case it is assumed that all the faces detected in particular photo are characterized with the same emotion label as the whole image. The standard fine-tuning procedure was implemented: we removed the last (classification) layer, added a bottleneck fully-connected layer with 1024 neurons, dropout layer with probability 0.5 and final fully-connected classifier for 3-class classification problem. The following hyperparameters were chosen: learning rate 1e-4, Adam optimizer, batch size = 16. We trained such networks for 100 epochs with standard data augmentation: random crops, scale and horizontal flip with probability 0.5. The final decision is made by the simple voting of the classifier outputs for individual faces.

In Table 2 we report the comparative analysis of different methods which we explored during the EmotiW challenge. Here we marked by italic the individual classifiers, which are the members of the final ensemble.

Table 2: Comparison of various classifiers on the validation data

Method	Accuracy
CENTRIST, SVM [6] (baseline)	52.97%
VGG-16 (end-to-end)	64.11%
VGG-19 (end-to-end)	27.64%
VGGFace (end-to-end)	65.42%
VGGFace features, SVM	64.90 %
ResNet-50 (end-to-end)	62.65%
Xception (end-to-end)	60.18%
VGGFace features, Logistic Regression	67.24%
VGGFace features, SVM	65.41%
VGGFace features, Multi-Layered Perceptron (1 hidden layer)	68.09%
VGGFace features (BGR, avgpool), Gradient Boosting Tree	69.53%
<i>VGGFace features (RGB, fc7), Random Forest</i>	67.62%
<i>VGGFace features (BGR, fc7), Random Forest</i>	68.18%
<i>VGGFace features (RGB, avgpool), Random Forest</i>	69.78%
<i>VGGFace features (BGR, avgpool), Random Forest</i>	70.11%
<i>Landmark features, Random Forest</i>	65.16%
<i>VGG-16 for the whole image</i>	65.89%
Proposed ensemble (except the VGG-16 for the whole image)	72.77%
Proposed ensemble, Tiny faces	66.51%
Proposed ensemble, HOG/Viola-Jones faces	75.39%

Based on these results, we can draw the following conclusions. First, the end-to-end deep CNNs are better than the baseline, however they are worth than the classifiers in our

ensemble. It can be explained as wrong assumption that if an image contains particular face, then face share the same emotion label as image. Moreover, this approach is not designed to model scene context which has significant influence on the group emotion label.

Second, it should be noted that using the Tiny Face Detector [16] in ensemble of classifiers causes 9% less accuracy when compared to the final pipeline with traditional face detection techniques from DLIB and OpenCV libraries. This significant degradation may be caused by the We think that the reason for such poor quality is the data which was used for training VGGFace [10]. The network was trained on rather large facial regions of the high quality (without occlusions, background cluttering, etc.) and is not appropriate for very small faces. Thus, the problem can be solved by replacing the pre-trained VGGFace feature extractor with another feature extractor, specially learned to identify tiny faces.

Thirdly, we examined that the recognition accuracy can be improved by adding new classifier into ensemble if its sole accuracy is rather high (not less than 65%). For example, adding the weak classifier (VGG-16 trained for the whole group image) made it possible to decrease error rate approximately 3%.

Finally, the proposed pipeline (Fig. 2) achieves **75.4%** accuracy on the validation set. The confusion matrix of our ensemble is presented in Fig. 3. One can note that our approach performs better on Negative and Positive classes rather than on Neutral one. It can be explained because the neutral group emotion is much more difficult to define. The same effect we observed while testing practically all other models. The only one exception is the processing of tiny faces [16], for which we obtained practically identical accuracy (66-67%) for each class.

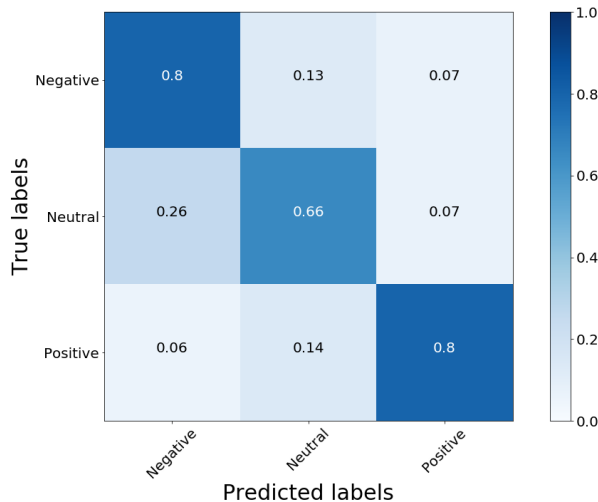


Figure 3: Confusion matrix of the final solution.

4 CONCLUSIONS

In this paper we describe a solution used by our team for the group-level emotion recognition sub-challenge of EmotiW2017. Our algorithm (Fig. 2) includes detecting faces using classical Viola-Jones cascades and HOG features, detecting facial

landmarks, extracting facial features using deep CNN trained for face identification task, computing the median of these features in order to deal with arbitrary number of faces in a group photo. The final decision is obtained by an ensemble of weighted Random Forest classifiers.

It is necessary to highlight that the training set of emotional images was used only to train the individual Random Forests. Hence, our method is not end-to-end, because the EmotiW 2017 dataset is not so large to learn competitive feature extractor. Our approach benefits from aggregating face representations without associating each of them with the label of the whole image. We have found that this particular approach can be useful for ‘in the wild’ group images, where it is not always true that each person shares the same emotion of a group.

Our pipeline achieved 75.4% classification accuracy on the validation data, which is practically 23% higher when compared to the baseline (CENTRIST feature detector and SVM [6]). Our model achieves 78.53% on the Test set (compare to 53.62% of the baseline with CENTRIS descriptors). Our Keras code is publicly available at <https://github.com/arassadin/emotiw2017>.

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