Emotion Recognition From Facial Expressions

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Abstract

Facial emotion recognition (FER) is a topic of significant frontier and ongoing debate, not only in our daily lives but also in the fields of artificial intelligence (AI) and computer vision. However, the existing FER approaches are not always reliable or explainable, we here propose our model with interpretations, i.e., via layer activations, CAM, and Grad-CAM. Empirical results on FER benchmarks show that our model can achieve comparable state-of-the-art performance in terms of the accuracy. Our code and supplementary material are available at https://github.com/werywjw/SEP-CVDL.

1. Introduction

Facial emotion recognition (FER) [6, 7] is a topic of significant frontier and ongoing debate, not only in our daily lives but also in the fields of *artificial intelligence* (AI) and computer vision. In this report, we aim to leverage several *deep neural networks* (DNNs), which contain convolution layers and residual/attention blocks, to detect and interpret six basic universally recognized and expressed human facial emotions (i.e., happiness, surprise, sadness, anger, disgust, and fear). To make our model more transparent, we explain this emotion classification task with *class activation mapping* (CAM) and *gradient-weighted class activation mapping* (Grad-CAM).

Our main contributions can be summarized as follows.

- We collect and preprocess the training and testing data (image and video) from various public databases.
- We implement all CNN models from scratch and optimize it with different augmentation techniques. Meanwhile, we provide the classification scores of each emotion class in a comprehensive CSV file with respect to each image.
- We give the video demo to illustrate the real-world performance of our best model.
- We provide qualitative benefits such as interpretability to explain our model with Grad-CAM.

The structure of this report is arranged as follows. Section 2 contains the related work of our research. In Section 3, we address the datasets we collected and the model architecture we implemented. The preliminary evaluation results of our models are given in Section 4.4. Section 5 describes the optimization strategies we plan to investigate in the coming weeks. Figure 3 illustrates the empirical results of our current best model.

2. Related Work

2.1. Facial Emotion Recognition

2.2. Explainable AI

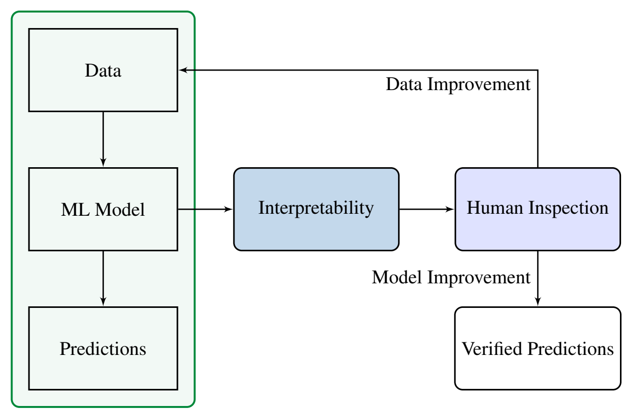

Figure 1. Overview of the traditional standardized ML evaluation process (see the illustration in the large green box) and the explainable AI pipeline

2.3. CAM and Grad-CAM

In generally, CAM [18] helps interpret CNN decisions by providing visual cues about the regions that influenced the classification, as it highlights the important regions of an image or a video, aiding in the understanding of the behavior of the model, which is especially useful for model debugging and further improvement. Besides proposing a method to visualize the discriminative regions of a CNN trained for the classification task, we adopt this approach from Zhou et al. [18] to localize objects without providing the model with any bounding box annotations. The model can therefore learn the classification task with class labels and is then able to localize the object of a specific class in an image or video.

CAM is a technique popularly used in CNNs to visualize and understand the regions of an input image that contribute the most to a particular class prediction. Typically, CAM is applied to the final convolutional layer of a CNN. In our case, we leverage the fifth convolutional layer of our model to generate the CAM heatmap. The *global average pooling* (GAP) layer, which computes the average value of each feature map to obtain a spatial average of feature maps, is used to obtain a spatial average of the feature maps.

Despite CAM can provide valuable insights into the decision-making process of deep learning models, especially CNNs, CAM must be implemented in the last layer of a CNN or before the fully connected layer, We will meanwhile compare to Gradient-weighted CAM [15], introduced as a technique that is easier to implement with different architectures. This task will be implemented by using the libraries from PyTorch and OpenCV [1].

Chattopadhay et al. [2] proposed Grad-CAM++,

3. Approach

4. Evaluation

4.1. Experimental Setup

All the experiments are implemented in Python and Shell for generating scripts. For evaluation, we use the metric accuracy. We report all the training, testing, and validation accuracy in % to compare the performance of our models. The loss function employed for all models is cross-entropy (CE), which is typically for multi-class classification. That is:

$$\mathcal{L}_{\text{CE}} = -\sum_{i=1}^{n} y_i \log(p_i), \tag{1}$$

where y_i is the true label and p_i is the predicted probability of the i-th class.

4.2. Dataset Description

To initiate the project, we acquired the databases such as RAF-DB [8, 9], FER+ [1], CK+ [11], TFEID [3, 10], as well as the video database DISFA [12]. Based on these databases, we created a dataset by augmentation to increase the variety, and full details of augmentation (see Section 5.1). In terms of illustrating the content of used pictures, we exclusively analyze human faces representing 6 emotions. That is, we generalized a folder structure annotating the labels 0 (happiness), 1 (surprise), 2 (sadness), 3 (anger), 4 (disgust), and 5 (fear). Besides the original format of images and videos, we set standards for extracting frames from the videos, resizing training pictures to 64×64 pixels, and saving them in the JPG format.

The images are converted to greyscale with three channels, as our original *convolutional neural network* (CNN) is designed to work with three-channel inputs with random rotation and crop. Emotions were assigned tags to each individual picture in a CSV file to facilitate further processing in the model. We create a custom dataset, which is a collection of data relating to all training images we collected, using PyTorch.

4.3. Model Architecture

The input to our emotion recognition model is a gray scale image at 64×64 resolution. The output is 6 emotion classes: happiness, surprise, sadness, anger, disgust, and fear. We implement an emotion classification model from scratch with four convolution layers at the very beginning. Following each convolutional layer, batch normalization and interleaved with max pooling are used, as this stabilizes learning by normalizing the input to each layer. Afterward, three linear layers are applied to extract features to the final output. We also add a 50% dropout layer to prevent overfitting. Verified by Barsoum et al. [1], the dropout layers are effective in avoiding model overfitting. The activation function after each layer is *Rectified Linear Unit* (ReLU), since it introduces the non-linearity into the model, allowing it to learn more complex patterns.

In order to find the best hyperparameter configuration (see Table 4 for details) of the model, we utilize the parameter grid from sklearn. Additionally, we increase the depth of the network by adding some convolutional layers to learn more complex features. To help the training of deeper networks more efficiently, we add the residual connections, as they allow gradients to flow through the network more easily, improving the training for deep architectures. Moreover, we add *squeeze and excitation* (SE) blocks to apply channel-wise attention.

4.4. Results

Adding a extra convolutional layer to the model with much more parameters does not necessarily lead to better performance. Batch normalization can indeed improve the performance of the model.

Figure 2 shows the test result aggregated from the database RAF-DB [4] and FER2013 [14]. Different combinations of functions from the `pytorch.transforms` library are tested for augmentation from those already established filters. As seen in Table 1, our CNN without random augmentation outperforms the other models in terms of accuracy, indicating that this kind of augmentation is not able to help our model predict the correct label, thus we later aim to optimize with other augmentation techniques to capture more representative features of different emotions.

[1] https://opencv.org

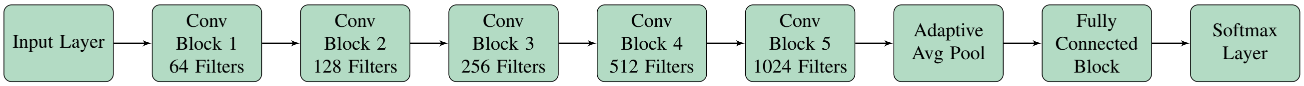

Figure 2. Overview of the model architecture (see Figure 3 for a detailed version)

DATASET	MODELS	ARCHITECTURE	ACCURACIES			# PARAMETERS
			Training	Testing	Validation	
RAF-DB [8, 9]	ResNet18 [5]	Residual Block	**98.9**	81.3	67.9	11179590
	Ours (13 layers)	+BN-SE	96.6	80.6	66.8	2606086
	Ours (10 layers)	-BN-SE	96.3	76.9	60.6	10474118
	Ours (16 layers)	+BN+SE	98.4	81.7	71.1	10478598
	Ours (15 layers)	+BN-SE	98.6	**83.1**	**72.1**	10478086
	Ours (17 layers)	+BN-SE	97.5	82.5	70.0	41950726
FER2013 [1]	Ours (13 layers)	+BN-SE	86.6	64.1	40.2	2606086
	Ours (15 layers)	+BN-SE	89.6	**65.6**	40.7	10478086
	Ours (17 layers)	+BN-SE	**96.0**	65.5	**41.6**	41950726

Table 1. Accuracies (%) for different models (with specific architectures and numbers of parameters) in our experiments (Note that SE stands for the squeeze and excitation block and BN for the batch normalization; +/- represent with/without respectively)

Further research is orientated on papers engaging similar investigations [9, 16, 17].

5. Optimization Strategies

5.1. Data Augmentation

In deep learning and AI, augmentation stands as a transformative technique, empowering algorithms to learn from and adapt to a wider range of data. By introducing subtle modifications to existing data points, augmentation effectively expands the dataset, enabling models to generalize better and achieve enhanced performance. As models encounter slightly altered versions of familiar data, they are forced to make more nuanced and robust predictions. With this process, we aim to prevent overfitting, which is a common pitfall in machine learning. Additionally, we guide the training process to enhance the recognition and handling of real-world variations. Meanwhile, we create various replications of existing photos by randomly altering different properties such as size, brightness, color channels, or perspectives.

5.2. Classification Scores

To further analyze the separate scores of each class of the model, we write a script that takes a folder path as input and iterates through the images inside a subfolder to record the performance of the model with respect to each emotion class. This CSV file is represented with the corresponding classification scores.

6. Conclusion and Discussion

7. Limitation

Author Contributions

Equal contributions are listed by alphabetical order of surnames. Every author did the literature research and contributed to the writing of the paper.

- **Tanja Jaschkowitz** implemented the model architecture, training and testing infrastructure, and CSV file aggregations.
- **Leah Kawka** collected the training data, prepared data processing, implemented augmentation, and ran the results. She also takes part in the explainable AI and Grad-CAM.
- **Mahdi Mohammadi** implemented the augmentation, did the research searching, conclusion reasearching, data preprocessing, and CAM-Images inquiry.
- **Jiawen Wang** implemented the model architecture, training and testing infrastructure, classification score script, and optimization strategies. In the specific writing part, she drew the figures and tables and improved this report from team members.

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filepath	happiness	surprise	sadness	anger	disgust	fear
archive/RAF-DB/test/test_0524_aligned_happiness.jpg	**1.00**	0.00	0.00	0.00	0.00	0.00
archive/RAF-DB/test/test_0093_aligned_happiness.jpg	**1.00**	0.00	0.00	0.00	0.00	0.00
archive/RAF-DB/test/test_2193_aligned_sadness.jpg	0.03	0.01	**0.90**	0.01	0.02	0.04
archive/RAF-DB/test/test_1214_aligned_happiness.jpg	**1.00**	0.00	0.00	0.00	0.00	0.00
archive/RAF-DB/test/test_1816_aligned_surprise.jpg	0.00	**1.00**	0.00	0.00	0.00	0.00
archive/RAF-DB/test/test_0294_aligned_surprise.jpg	0.01	**0.99**	0.00	0.00	0.00	0.00
archive/RAF-DB/test/test_1128_aligned_happiness.jpg	**1.00**	0.00	0.00	0.00	0.00	0.00
archive/RAF-DB/test/test_1799_aligned_sadness.jpg	0.37	0.02	**0.45**	0.02	0.1	0.03
archive/RAF-DB/test/test_0610_aligned_sadness.jpg	0.02	0.00	**0.74**	0.02	0.21	0.01
archive/RAF-DB/test/test_1373_aligned_anger.jpg	0.00	0.00	0.00	**1.00**	0.00	0.00
archive/RAF-DB/test/test_1788_aligned_fear.jpg	0.00	0.00	0.00	0.00	0.00	**1.00**
archive/RAF-DB/test/test_0007_aligned_disgust.jpg	0.03	0.05	0.03	**0.58**	0.18	0.13
archive/RAF-DB/test/test_0804_aligned_disgust.jpg	0.02	0.00	0.18	0.02	**0.77**	0.00

Table 2. Overview of our random testing results examples extracted from the CSV file

Dataset	#Images in training set	#Images in testing set	# Video/Images in validation set
Denver Intensity of Spontaneous Facial Action Database (DISFA [13])	-	-	27
Real-world Affective Faces Database (RAF-DB [8, 9])	9747	2388	600
Facial Expression Recognition 2013 (FER2013 [1])	23743	5945	600
Extended Cohn-Kanade Dataset Plus (CK+ [11])	309	-	600
Taiwanese Facial Expression Image Database (TFEID [3, 10])	229	-	600

Table 3. Overview of the datasets statistics used in our experiment

Hyperparameter	Value
Learning rate	$\{0.01, 0.001, 0.0001\}$
Batch size	$\{8, 16, 32, 64\}$
Dropout rate	$\{0.2, 0.5\}$
Epoch	$\{20, 30, 40\}$
Early stopping	{`True`, `False`}
Patience	$\{5\}$

Table 4. Explored hyperparameter space for our models

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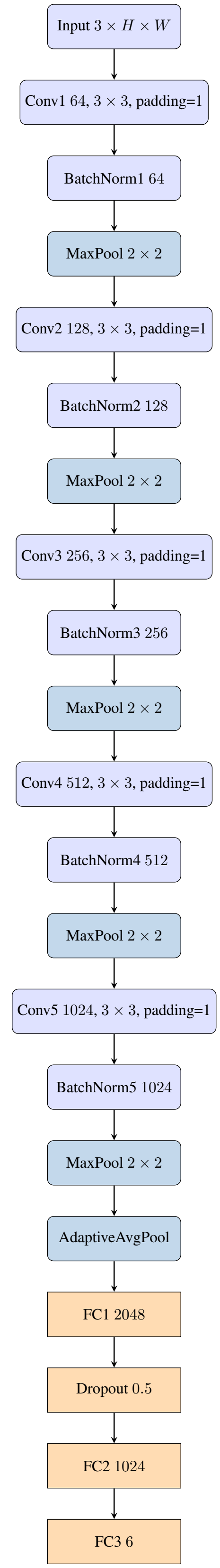

Figure 3. Overview of our detailed model architecture