RAF-DB Facial Expression Recognition

Fan Yixuan

Department of Electronic Engineering, Tsinghua University

June 6, 2022



Method

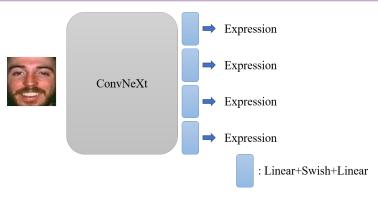


Figure 1: The distribution of the training samples from the seven expressions is sparse in the high-dimensional space, which leads to overfitting. Thus, the feature vector used for classification is divided into several sub-vectors and the corresponding classification heads are **ensembled**. If **channel of CNN** can be viewed as an equivalent structure of **token of Transformer**, it is similar to DeiT. It is also very similar to dropout, but shows superior performance on this dataset (+0.59%).

2 / 13

Experimental Results: Accuracy 90.97%

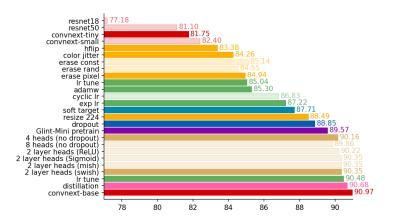


Figure 2: We achieve a performance that is competitive with SOTA (while using less external data) by stacking general tricks for image recognition. Structurally, we use a modern CNN without any attention-based modules and propose a plug-and-play multi-head trick.

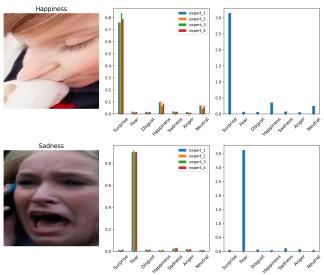
Compare to SOTA

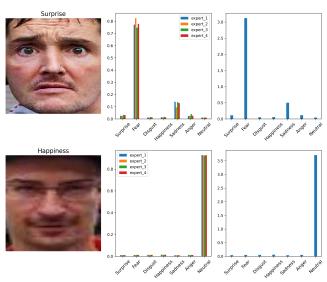
Method		Acc	Comment
RAN [8]	TIP 2020	86.90	
SCN [7]	CVPR 2020	87.03	
DACL [1]	WACV 2021	87.78	
KTN [2]	TIP 2021	88.07	
PSR [6]	CVPR 2020	88.98	
DMUE [4]	CVPR 2021	89.42	
FDRL [3]	CVPR 2021	89.47	
ARM [5]	arXiv 2021	90.42	Wrong approach with information disclo-
			sure.
TransFER [9]	ICCV 2021	90.91	Stacking IR50, 'Local CNN' and 8 layers of
			ViT, no code available.
POSTER [10]	arXiv 2022.4	92.05	Need a well-trained keypoint detector, no
			code available.
Ours		90.97	

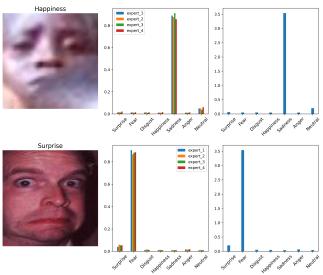
Confusion Matrix

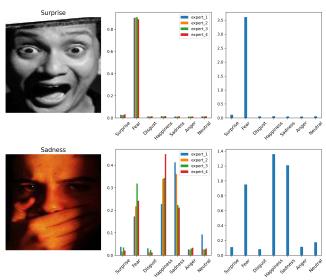


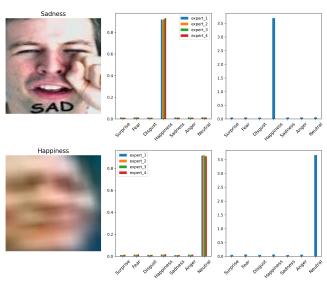
Figure 3: The vertical axis is the true label, and the horizontal axis is the predicted label.











- Amir Hossein Farzaneh and Xiaojun Qi.
 Facial expression recognition in the wild via deep attentive center loss.
 In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pages 2402–2411, 2021.
- [2] Hangyu Li, Nannan Wang, Xinpeng Ding, Xi Yang, and Xinbo Gao. Adaptively learning facial expression representation via cf labels and distillation. IEEE Transactions on Image Processing, 30:2016–2028, 2021.
- [3] Delian Ruan, Yan Yan, Shenqi Lai, Zhenhua Chai, Chunhua Shen, and Hanzi Wang. Feature decomposition and reconstruction learning for effective facial expression recognition. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 7660–7669, 2021.
- Dive into ambiguity: latent distribution mining and pairwise uncertainty estimation for facial expression recognition.

 In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 6248–6257, 2021.
- [5] Jiawei Shi, Songhao Zhu, and Zhiwei Liang. Learning to amend facial expression representation via de-albino and affinity. arXiv preprint arXiv:2103.10189, 2021.

Jiahui She, Yibo Hu, Hailin Shi, Jun Wang, Qiu Shen, and Tao Mei.

- [6] Thanh-Hung Vo, Guee-Sang Lee, Hyung-Jeong Yang, and Soo-Hyung Kim. Pyramid with super resolution for in-the-wild facial expression recognition. *IEEE Access*, 8:131988–132001, 2020.
- Kai Wang, Xiaojiang Peng, Jianfei Yang, Shijian Lu, and Yu Qiao.
 Suppressing uncertainties for large-scale facial expression recognition.
 In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 6897–6906, 2020.

[4]

- [8] Kai Wang, Xiaojiang Peng, Jianfei Yang, Debin Meng, and Yu Qiao. Region attention networks for pose and occlusion robust facial expression recognition. IEEE Transactions on Image Processing, 29:4057–4069, 2020.
- [9] Fanglei Xue, Qiangchang Wang, and Guodong Guo.
 Transfer: Learning relation-aware facial expression representations with transformers.

 In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), pages 3601–3610, October 2021.
- [10] Ce Zheng, Matias Mendieta, and Chen Chen. Poster: A pyramid cross-fusion transformer network for facial expression recognition. arXiv preprint arXiv:2204.04083, 2022.

Thanks!