Feature Pyramid Network for Multi-task Affective Analysis

Ruian He, Zhen Xing, Weimin Tan, Bo Yan
School of Computer Science,
Shanghai Key Laboratory of Intelligent Information Processing, Fudan University
{rahe16, xingz20, wmtan14, byan}@fudan.edu.cn

Abstract

Affective Analysis is not a single task, and the valence-arousal value, expression class, and action unit can be predicted at the same time. Previous researches did not pay enough attention to the entanglement and hierarchical relation of these three facial attributes. We propose a novel model named feature pyramid networks for multi-task affect analysis. The hierarchical features are extracted to predict three labels and we apply a teacher-student training strategy to learn from pretrained single-task models. Extensive experiment results demonstrate the proposed model outperforms other models. This is a submission to The 2nd Workshop and Competition on Affective Behavior Analysis in the wild (ABAW). The code and model are available for research purposes at this link.

1. Introduction

Numerous researches have been conducted on affective analysis for years and aim to automatically comprehend human feelings, emotions, and behaviors. Affect analysis contributes to many applications, such as psychological therapy and marketing analysis.

We participate in the 2nd Workshop and Competition on Affective Behavior Analysis in-the-wild (ABAW).[11][15][16][13][12][17][14][42] And there are three challenges in affective analysis: valence-arousal, seven basic expression and action unit prediction. Valence-arousal value is a description of human expression, and there are positive and negative for valence and high and low in arousal. Seven basic expressions[11] are defined as Anger, Disgust, Fear, Happiness, Sadness, Surprise, and Neutral here. All facial movement can be categorized in different action units in terms of the Facial Action Coding System (FACS) model[3].

The model we propose is named feature pyramid networks for multi-task affective analysis. It is an image-based method and can solve the three tasks above at the same time. And we use Feature Pyramid Network[22] for the backbone and the connection between feature layers can bring feature fusion merits. And we will cover this in section 3.

We use the cropped and aligned images from Aff-Wild2 dataset provided by ABAW2 as the training and validation set. There are a great number of missing labels in the provided AffWild2 dataset. Many samples only have labels for one or two tasks. So we augment the dataset with ExpW(Expression-in-the-Wild)[45] and AffectNet[29] and follow the method in semi-supervised learning and propose a teacher-student training procedure to train a multi-task model. We will get into details in section 4.

Finally, our contributions can be concluded as follows:

1. We propose a novel model using the feature pyramid network for multi-task affective analysis. It exploits the entanglement and hierarchical relation of these three facial attributes.

2. We apply a teacher-student training procedure to learn from missing labels. This allows the multi-task model to learn from all labels in the Aff-Wild2 dataset at the same time.

3. We achieve an excellent result on the Aff-Wild2 validation set over the official baseline[11] and other models.
2. Related Works

Typically, according to the type of extracted features, FER algorithms can be categorized into hand-crafted feature-based and deep learning-based methods. Hand-crafted features can be further divided into texture-based features, geometry-based features, and hybrid features. The texture-based features mainly contain Gabor [23], SIFT [30], HOG [2], LBP [32], NMF [47], etc. The geometry-based features are primarily based on facial landmark points. Hybrid features refer to the combination of the two above-mentioned features. In the past few years, large-scale facial expression datasets, such as RAF-DB [19] and AffectNet [29], greatly facilitate deep FER research. Very recently, Zeng et al. [44] first considered the inconsistent annotation problem in FER research. Wang et al. [38] suppressed the uncertainties and improved the FER performance. Li et al. [18] considered the long-tail distribution and high similarity in FER datasets and achieved leading performance.

The task of facial action unit detection is to recognize active action units. Generally, action units detection methods can be described into two groups: patch-based methods and structure-based methods. Patch-based methods target to extract local features from important facial regions. Zhao et al. [46] proposed a region layer to induce important facial regions for extracting local features. In [20][21], Li defined regions of interest (ROI) according to facial landmarks and designed individual convolutional layers to learn deeper features for each facial region. Shao et al. [34] applied multi-scale region learning to extract AU-related local features. Recently, structure-based methods [31][4][36] tend to use CNNs and GCNs to extract the local information and capture the relationship between AUs respectively.

Multi-task learning in computer vision is aimed at improving the generalization ability of network on related tasks, e.g. surface normal estimation and edge labels [39], camera pose estimation and wide baseline matching [43], person attribute classification [25] etc. MTL networks can also be divided into two categories. The methods of first category target to find which part of the baseline should be shared and which part should be task-specific [24][27][28][33][1], while the methods of second category make task grouping by taking task-similarity into account [40][8][9][25][26].

3. Multi-task Feature Pyramid Network

Valence-arousal, expression, and facial action units are not all about extracted top features. The low-level features which contain local information can also help with classification. So we exploit the pyramid network to predict affective labels.

Since the three tasks all describe affective behaviors, they are closely related. Specifically, expression categories and valence-arousal describe affective behaviors globally, while action units reflect the local facial movements. For example, the occurrence of AU6 and AU12 is a sign of happiness [5], while happy images always have high valence scores[29].

There are a few earlier works concerning the use of feature pyramid in facial expression recognition[41][37]. However, they only focus on a single task and we show that the feature pyramid also works for multi-task affective analysis.

3.1. Network Architecture

Our network architecture can be displayed as figure 1. We follow the implementation of Feature Pyramid Networks to build our model[22]. The input image is feed into the ResNet [6] backbone first and extract conv2, conv3, conv4, and conv5 output. Then the top-down feature fusion is applied. The up-layer features are scaled by 2 and added to the down-layer. We do average pooling in all four layers to get 1×1 output per layer. Finally, features from all layers are concatenated to form a vector used for classification.

3.2. Multi-task learning

We use three different classification heads for the three tasks respectively. For the valence-arousal task, we use a linear layer and mean squared error (MSE) loss function. The valence-arousal task is a regression task and it is expected to predict values between -1 and 1 for valence and arousal intensity. Compared to mean absolute error (MAE), MSE has more tolerance for small deviation which is good for being not overfitting. The loss can be calculated as:

\[ L_{VA}(x, y) = (x - y)^2 \]

in which \(x\) and \(y\) stand for the prediction and ground truth of valence and \(x, y\) stand for the prediction and ground truth of arousal.

For the expression task, we use the cross-entropy loss function for this multi-class prediction. And for the facial action unit task, we use binary cross-entropy loss function for this multi-label prediction. It is a typical solution for expression classification. The CE and BCE loss can be calculated as:

\[ L_{EXPR}(x, y) = -x[y] + \log(\sum_j \exp(x[j])) \]

\[ L_{AU}(x, y) = \sum_j (y_j \log(\sigma(x_j)) + (1 - y_j) \log(\sigma(1 - x_j))) \]
In cross-entropy loss, $y$ is the class number and in binary cross-entropy loss, $y$ is the 0-1 binary vector.

Our total loss function for the multi-task model can be shown as:

$$L_{\text{Multi}} = \alpha L_{VA} + \beta L_{EXPR} + \gamma L_{AU}$$

And we finally choose $\alpha = \beta = \gamma = 1$ for training. All three classification heads only have one linear layer and share the same backbone. We expect the backbone network to learn unified distinguishable features of expression. And three heads get features from all four layers in FPN.

4. Learning from Missing and Unbalanced Labels

4.1. Data Augmentation

Aff-Wild2, the dataset we mainly use for the ABAW2 Competition, is annotated for three affective behavior analysis tasks: valence-arousal estimation, basic expression classification, and facial action unit detection.

For expression classification, we can observe a severe imbalance distribution in figure 2. Re-balancing is a frequently-used strategy to deal with long-tail distribution, but it will cause under-fitting to the head or over-fitting to the tail. So we just merge samples of Aff-Wild2, ExpW [45] and AffectNet [29] without re-sampling. The distributions of seven emotion categories in the Aff-wild2 dataset, the ExpW dataset, the AffectNet dataset, and the merged dataset are shown in figure 2.

For valence-arousal estimation, we import the AffectNet dataset which contains 280,000 images annotated with valence-arousal scores in [-1, 1]. Cause we regard it as a regression problem, we do not apply any re-balancing strategies.

4.2. Training Strategies

We use teacher-student network to fix missing labels. The similar work is [35], and we also use multi-teacher-single-student(MTSS) strategy but in a simpler way. The process can be displayed as figure 3. The teacher model is a single-task model and student model is a multi-task model. We don’t match the feature space but just use the single-task teacher model to predict the missing label. The multi-task student network shares the same structure of the teacher model but has several classification/regression heads to learn general features for all three expression recognition at the same time. And the process can also be showed as the following algorithm:

**Algorithm 1 Teacher-student Training Strategy**

```plaintext```
run preprocessing scripts for mixing AffWild2, ExpW and AffectNet datasets. The dataset $D_{\text{mixed}}$ is different for each task.
for data type $t \in \{VA, EXPR, AU\}$ do
    train single teacher model $\phi_t$ for each task.
    predict label $L_t$ for every image in AffWild2 dataset.
end for
build unified AffWild2 dataset $D_{\text{multi}}$ from predicted labels $L_t, t \in \{VA, EXPR, AU\}$. 
train student multi-task model $\phi_{\text{multi}}$ in $D_{\text{multi}}$. 
return $\phi_{\text{multi}}$
```

We limit the batch of each epoch to 25% to avoid over-fitting. As the AffWild2 dataset is combined with video frames, there are a lot of redundant labels for each task. The differences between frames are not obvious enough to provide more information to train the model. So we reduce the steps of each epoch to 25% of the whole training set. That is to say in each epoch we randomly get 25% samples of

Fig. 2. Comparison of different basic expression distributions. It shows the label distribution of the three datasets.

Fig. 3. Teacher-student Training Strategy. The teacher model is a single task model and the student model is a multi-task model. In this situation, the VA label is missing and our single-task model provides the soft label for the multi-task model. So the multi-task model can learn from all three labels simultaneously.
Table 1. Experiments on AffWild2 Validation Set. VA,EXPR, and AU mean the score for each task. CCC, F1, Acc, and score follow the rule that the higher the better. For different input data, Single is the origin AffWild2 dataset. Mixed is our augmented dataset. And Multi is the AffWild2 dataset with our generated soft labels.

| Model            | Data | CCC-A | CCC-V | VA  | Acc | F1   | EXPR | Acc | F1   | AU  |
|------------------|------|-------|-------|-----|-----|------|------|-----|------|-----|
| Baseline[11]     | Single | 0.23  | 0.21  | 0.22 | 0.50 | 0.30 | 0.36 | 0.22 | 0.4  | 0.31 |
| MobileNet        | Single | 0.34  | 0.12  | 0.23 | 0.50 | 0.29 | 0.36 | 0.87 | 0.39 | 0.63 |
| ResNet           | Single | 0.29  | 0.14  | 0.22 | 0.52 | 0.30 | 0.38 | 0.86 | 0.41 | 0.64 |
| F3R(Ours)        | Single | 0.27  | 0.22  | 0.24 | 0.55 | 0.31 | 0.39 | 0.87 | 0.43 | 0.65 |
| MobileNet        | Mixed  | 0.31  | 0.27  | 0.29 | 0.58 | 0.36 | 0.43 | 0.87 | 0.37 | 0.62 |
| ResNet           | Mixed  | 0.28  | 0.23  | 0.26 | 0.57 | 0.36 | 0.43 | 0.87 | 0.41 | 0.64 |
| F3R(Ours)        | Mixed  | 0.34  | 0.31  | 0.32 | 0.59 | 0.37 | 0.44 | 0.87 | 0.37 | 0.64 |
| F3R(Ours)        | Multi  | 0.44  | 0.28  | 0.36 | 0.61 | 0.40 | 0.47 | 0.88 | 0.40 | 0.64 |

The training set. And that makes the training process more smooth and robust.

The model network is trained on an NVIDIA RTX2080 GPU. For a single-task model, the network is trained for 40 limited epochs and it cost 3 hours. And for the multi-task model, it cost 1 day for training 20 full epochs. We use Adam optimizer[10] at a learning rate of 1e-3. And the batch size is set to 128.

5. Experiment

We have done extensive experiments on the validation set of the AffWild2[11][15][16][13][12][17][14][42]. We have compared our model with typical classification models such as MobileNet[7] and ResNet [6]. We use pretrained model of MobileNet and ResNet and FPN for both student model and teacher model. We also refer to the official baseline on the top, which is taken from the paper[11].

We have also tested on different data settings. Firstly, we only train on the original dataset and then on our augmented dataset. At last, we use the teacher-student training strategy to train a multi-task model. The quantitative results can be found in table 1.

5.1. Metrics

For evaluation, we follow the settings in the baseline paper [11]. The metrics are CCC, F1, and TAcc. The Concordance Correlation Coefficient(CCC) evaluates the agreement between two time series by scaling their correlation coefficient with their mean square difference. We use CCC to evaluate the prediction of the valence-arousal task. The CCC can be calculated as:

$$CCC = \frac{2 s_{xy}}{s_x^2 + s_y^2 + (\bar{x} - \bar{y})^2}$$  (5)

in which $s_{xy}$ is the covariance of prediction and ground truth and $s_x$ and $s_y$ are the separated variance.

The $F_1$ score is a weighted average of the recall (i.e., the ability of the classifier to find all the positive samples) and precision (i.e., the ability of the classifier not to label as positive a sample that is negative). $F_1$ score is used to evaluate the prediction of seven basic expression task.

$$F_1 = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$  (6)

And the average $F_1$ is denoted as $AF_1$, which means the average of all label predictions. And $AF_1$ is used to evaluate the task of action unit prediction.

Total accuracy (denoted as TAcc) is another metric for classification and it is defined on all test samples and is the fraction of predictions that the model got right. This is also used for expression and action unit tasks.

$$TAcc = \frac{\text{Correct Predictions}}{\text{All Predictions}}$$  (7)

The three tasks scores are calculated as follows, and they are the weighted sum of above metrics.

$$S_{VA} = 0.5 \times CCC_V + 0.5 \times CCC_A$$  (8)

$$S_{EXPR} = 0.67 \times F_1 + 0.33 \times TAcc$$  (9)

$$S_{VA} = 0.5 \times AF_1 + 0.5 \times TAcc$$  (10)

5.2. Results

From the table 1 we can see that data augmentation helps with almost every model. Firstly, we have done experiments on the bare AffWild2 dataset with our models. The result was mediocre. Then we supplemented the dataset with ExpW[45] and AffectNet[29] to make up for its lack of diversity. The data augmentation improved valence-arousal and expression prediction scores by approximately 10%.

And we used the best single-task model to generate a unified AffWild2 dataset for multi-task training. We applied
a teacher-student training strategy to train these models and all of them (Multi) are better than the single-task one (Single) in the bare AffWild2 dataset.

Compared to other models like MobileNet[7] and ResNet [6], our feature pyramid networks for multi-task affective analysis model outperforms by 2% to 10%. Though the improvement is not as significant as manipulating the data, it is still better than ResNet which has the same amount of parameters.

We also visualize the contribution of each layer to the classification in our multitask model as figure 4. We sum all the absolute weight in the classification head connected to the specific layer and multiply it with the relative size of the input tensor. The figure shows that every task has a preference on feature selection, e.g. VA relies on layer1 and AU relies on the last two layers. Our backbone provides the hierarchical features and the classification head learns to choose critical features.

6. Conclusion

We propose a novel model using the feature pyramid network for multi-task affective analysis. The model exploits the hierarchical features in the backbone network and makes predictions for three different tasks, This model outperforms other classification models and the official baseline.

We also use a teacher-student training strategy to learn from missing labels in the dataset. It allows the model to learn from all three labels simultaneously. Without this strategy, multi-task learning won’t take effect.

Though the model has an excellent result, the mechanism behind is not quite studied. The feature selection in the classification head is not clear and needs further researches. And this model is not robust for side faces and occluded faces. More facial prior should be added to have a full understanding of the human face.

References

[1] Felix J. S. Bragman, Ryutaro Tanno, Sébastien Ourselin, Daniel C. Alexander, and Manuel Jorge Cardoso. Stochastic filter groups for multi-task cnns: Learning specialist and generalist convolution kernels. In 2019 IEEE/CVF International Conference on Computer Vision, ICCV 2019, Seoul, Korea (South), October 27 - November 2, 2019, pages 1385–1394. IEEE, 2019. 2
[2] N. Dalal and B. Triggs. Histograms of oriented gradients for human detection. In IEEE Computer Society Conference on Computer Vision & Pattern Recognition, 2005. 2
[3] P. Ekman and W. Friesen. Facial action coding system: a technique for the measurement of facial movement. 1978. 1
[4] Yingrui Fan, Jacqueline C. K. Lam, and Victor On Kwok Li. Facial action unit intensity estimation via semantic correspondence learning with dynamic graph convolution. In The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI 2020, The Thirty-Second Innovative Applications of Artificial Intelligence Conference, IAAI 2020, The Tenth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2020, New York, NY, USA, February 7-12, 2020, pages 12701–12708. AAAI Press, 2020. 2
[5] W. V. Friesen and P. Ekman. Emfacs-7: Emotional facial action coding system. 1983. 2
[6] Kaiming He, X. Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 770–778, 2016. 2, 4, 5
[7] Andrew G. Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, M. Andreetto, and Hartwig Adam. Mobilenets: Efficient convolutional neural networks for mobile vision applications. ArXiv, abs/1704.04861, 2017. 4, 5
[8] Laurent Jacob, Francis R. Bach, and Jean-Philippe Vert. Clustered multi-task learning: A convex formulation. In Daphne Koller, Dale Schuurmans, Yoshua Bengio, and Léon Bottou, editors, Advances in Neural Information Processing Systems 21, Proceedings of the Twenty-Second Annual Conference on Neural Information Processing Systems, Vancouver, British Columbia, Canada, December 8-11, 2008, pages 745–752. Curran Associates, Inc., 2008. 2
[9] Zhuoliang Kang, Kristen Grauman, and Fei Sha. Learning with whom to share in multi-task feature learning. In Lise Getoor and Tobias Scheffer, editors, Proceedings of the 28th International Conference on Machine Learning, ICML 2011, Bellevue, Washington, USA, June 28 - July 2, 2011, pages 521–528. Omnipress, 2011. 2
[10] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. CoRR, abs/1412.6980, 2015. 4
[11] Dimitrios Kollias, Irene Kotsia, Elmar Hajiyev, and Stefanos Zafeiriou. Analysing affective behavior in the second abaw2 competition, 2021. 1, 4
[12] D Kollias, A Schulc, E Hajiyev, and S Zafeiriou. Analysing affective behavior in the first abaw 2020 competition. In 2020 15th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2020), FG, pages 794–800. 1, 4

[13] Dimitrios Kollias, Viktoriia Sharmanska, and Stefanos Zafeiriou. Face behavior a la carte: Expressions, affect and action units in a single network. arXiv preprint arXiv:1910.11111, 2019. 1, 4

[14] Dimitrios Kollias, Viktoriia Sharmanska, and Stefanos Zafeiriou. Distribution matching for heterogeneous multi-task learning: a large-scale face study. arXiv preprint arXiv:2105.03790, 2021. 1, 4

[15] Dimitrios Kollias, Panagiotis Tzirakis, Mihalis A Nicolaou, Athanasios Papaioannou, Guoying Zhao, Björn Schuller, Irene Kontsa, and Stefanos Zafeiriou. Deep affect prediction in-the-wild: Aff-wild database and challenge, deep architectures, and beyond. International Journal of Computer Vision, pages 1–23, 2019. 1, 4

[16] Dimitrios Kollias and Stefanos Zafeiriou. Expression, affect, action unit recognition: Aff-wild2, multi-task learning and arcface. arXiv preprint arXiv:1910.04855, 2019. 1, 4

[17] Dimitrios Kollias and Stefanos Zafeiriou. Affect analysis in-the-wild: Valence-arousal, expressions, action units and a unified framework. arXiv preprint arXiv:2103.15792, 2021. 1, 4

[18] Hangyu Li, Nannan Wang, Xinpeng Ding, Xi Yang, and Xinbo Gao. Adaptively learning facial expression representation via C-F labels and distillation. IEEE Trans. Image Process., 30:2016–2028, 2021. 2

[19] S. Li, W. Deng, and J. P. Du. Reliable crowdsourcing and deep locality-preserving learning for expression recognition in the wild. In 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017. 2

[20] Wei Li, Farnaz Abtahi, Zhigang Zhu, and Lijun Yin. Eac-net: A region-based deep enhancing and cropping approach for facial action unit detection. In 12th IEEE International Conference on Automatic Face & Gesture Recognition, FG 2017, Washington, DC, USA, May 30 - June 3, 2017, pages 103–110. IEEE Computer Society, 2017. 2

[21] Wei Li, Farnaz Abtahi, Zhigang Zhu, and Lijun Yin. Eac-net: Deep nets with enhancing and cropping for facial action unit detection. IEEE Trans. Pattern Anal. Mach. Intell., 40(11):2583–2596, 2018. 2

[22] Tsung-Yi Lin, Piotr Dollár, Ross B. Girshick, Kaiming He, Bharath Hariharan, and Serge J. Belongie. Feature pyramid networks for object detection. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 936–944, 2017. 1, 2

[23] C. Liu and H. Wechsler. Gabor feature based classification using the enhanced fisher linear discriminant model for face recognition. IEEE Transactions on Image Processing A Publication of the IEEE Signal Processing Society, 11(4):467, 2002. 2

[24] M. Long and J. Wang. Learning multiple tasks with deep relationship networks. Computer Science, 2015. 2

[25] Yongxi Lu, Abbasheek Kumar, Shuangfei Zhai, Yu Cheng, Tara Javidi, and Rogério Schmidt Feris. Fully-adaptive feature sharing in multi-task networks with applications in person attribute classification. In 2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017, pages 1131–1140. IEEE Computer Society, 2017. 2

[26] Youssef A. Mejjaati, Darren Cosker, and Kwang In Kim. Multi-task learning by maximizing statistical dependence. In 2018 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2018, Salt Lake City, UT, USA, June 18-22, 2018, pages 3465–3473. IEEE Computer Society, 2018. 2

[27] Elliot Meyerson and Risto Miikkulainen. Beyond shared hierarchies: Deep multitask learning through soft layer ordering. In 6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings. OpenReview.net, 2018. 2

[28] Ishan Misra, Abhinav Shrivastava, Abhinav Gupta, and Martial Hebert. Cross-stitch networks for multi-task learning. In 2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016, pages 3994–4003. IEEE Computer Society, 2016. 2

[29] A. Mollahosseini, B. Hasani, and M. Mahoor. Affectnet: A database for facial expression, valence, and arousal computing in the wild. IEEE Transactions on Affective Computing, 10:18–31, 2019. 1, 2, 3, 4

[30] P. C. Ng and S. Henikoff. Sift: predicting amino acid changes that affect protein function. Nucleic Acids Research, 31(13):3812–3814, 2003. 2

[31] Xuesong Niu, Hu Han, Songfan Yang, Yan Huang, and Shiguang Shan. Local relationship learning with person-specific shape regularization for facial action unit detection. In IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16-20, 2019, pages 11917–11926. Computer Vision Foundation / IEEE, 2019. 2

[32] M. Pietikäinen, A. Hadid, G. Zhao, and T. Ahonen. [computational imaging and vision] computer vision using local binary patterns volume 40 — computer vision using local binary patterns. 10.1007/978-0-85729-748-8(Chapter 14):E1–E2, 2011. 2

[33] Sebastian Ruder, Joachim Bingel, Isabelle Augenstein, and Anders Søgaard. Latent multi-task architecture learning. In The Thirty-Third AAAI Conference on Artificial Intelligence, AAAI 2019, The Thirty-First Innovative Applications of Artificial Intelligence Conference, IAAI 2019, The Ninth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019, Honolulu, Hawaii, USA, January 27 - February 1, 2019, pages 4822–4829. AAAI Press, 2019. 2

[34] Zhiwen Shao, Zhilei Liu, Jianfei Cai, and Lizhuang Ma. Self: predicting amino acid changes that affect protein function. Nucleic Acids Research, 7(13):3812–3814, 2003. 2

[35] Elliot Meyerson and Risto Miikkulainen. Beyond shared hierarchies: Deep multitask learning through soft layer ordering. In 6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings. OpenReview.net, 2018. 2

[36] Matt Pietikäinen Anila Hadid, G. Zhao, and T. Ahonen. A database for facial expression, valence, and arousal computing in the wild. IEEE Transactions on Affective Computing, 10:18–31, 2019. 1, 2, 3, 4

[37] P. C. Ng and S. Henikoff. Sift: predicting amino acid changes that affect protein function. Nucleic Acids Research, 31(13):3812–3814, 2003. 2

[38] Xuesong Niu, Hu Han, Songfan Yang, Yan Huang, and Shiguang Shan. Local relationship learning with person-specific shape regularization for facial action unit detection. In IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16-20, 2019, pages 11917–11926. Computer Vision Foundation / IEEE, 2019. 2

[39] M. Pietikäinen, A. Hadid, G. Zhao, and T. Ahonen. [computational imaging and vision] computer vision using local binary patterns volume 40 — computer vision using local binary patterns. 10.1007/978-0-85729-748-8(Chapter 14):E1–E2, 2011. 2

[40] Sebastian Ruder, Joachim Bingel, Isabelle Augenstein, and Anders Søgaard. Latent multi-task architecture learning. In The Thirty-Third AAAI Conference on Artificial Intelligence, AAAI 2019, The Thirty-First Innovative Applications of Artificial Intelligence Conference, IAAI 2019, The Ninth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019, Honolulu, Hawaii, USA, January 27 - February 1, 2019, pages 4822–4829. AAAI Press, 2019. 2

[41] Zhiwen Shao, Zhilei Liu, Jianfei Cai, and Lizhuang Ma. Deep adaptive attention for joint facial action unit detection. In 2018 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2018, Salt Lake City, UT, USA, June 18-22, 2018, pages 3465–3473. IEEE Computer Society, 2018. 2
[35] Minchul Shin. Semi-supervised learning with a teacher-student network for generalized attribute prediction. *ArXiv*, abs/2007.06769, 2020. 3

[36] Tengfei Song, Lisha Chen, Wenming Zheng, and Qiang Ji. Uncertain graph neural networks for facial action unit detection. In *Thirty-Fifth AAAI Conference on Artificial Intelligence, AAAI 2021, Thirty-Third Conference on Innovative Applications of Artificial Intelligence, IAAI 2021, The Eleventh Symposium on Educational Advances in Artificial Intelligence, EAAI 2021, Virtual Event, February 2-9, 2021*, pages 5993–6001. AAAI Press, 2021. 2

[37] Wen Su, Haifeng Zhang, Yuan Su, and Jun Yu. Facial expression recognition with confidence guided refined horizontal pyramid network. *IEEE Access*, 9:50321–50331, 2021. 2

[38] Kai Wang, Xiaojiang Peng, Jianfei Yang, Shijian Lu, and Yu Qiao. Suppressing uncertainties for large-scale facial expression recognition. In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2020, Seattle, WA, USA, June 13-19, 2020*, pages 6896–6905. IEEE, 2020. 2

[39] Xiaolong Wang, David F. Fouhey, and Abhinav Gupta. Designing deep networks for surface normal estimation. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015*, pages 539–547. IEEE Computer Society, 2015. 2

[40] Ya Xue, Xuejun Liao, Lawrence Carin, and Balaji Krishnapuram. Multi-task learning for classification with dirichlet process priors. *J. Mach. Learn. Res.*, 8:35–63, 2007. 2

[41] Wei Yang, Hongwei Gao, Yueqiu Jiang, Jiahui Yu, Sun Jian, Jinguo Liu, and Zhaojie Ju. A cascaded feature pyramid network with non-backward propagation for facial expression recognition. *IEEE Sensors Journal*, 21:11382–11392, 2021. 2

[42] Stefanos Zafeiriou, Dimitrios Kollias, Mihalis A Nicolaou, Athanasios Papaioannou, Guoying Zhao, and Irene Kotzia. Aff-wild: Valence and arousal ‘in-the-wild’challenge. In *Computer Vision and Pattern Recognition Workshops (CVPRW), 2017 IEEE Conference on*, pages 1980–1987. IEEE, 2017. 1, 4

[43] Amir Roshan Zamir, Tilman Wekel, Pulkit Agrawal, Colin Wei, Jiendra Malik, and Silvio Savarese. Generic 3d representation via pose estimation and matching. In Bastian Leibe, Jiri Matas, Nicu Sebe, and Max Welling, editors, *Computer Vision - ECCV 2016 - 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part III*, volume 9907 of *Lecture Notes in Computer Science*, pages 535–553. Springer, 2016. 2

[44] Jiabei Zeng, Shiguang Shan, and Xilin Chen. Facial expression recognition with inconsistently annotated datasets. In Vittorio Ferrari, Martial Hebert, Cristian Sminchisescu, and Yair Weiss, editors, *Computer Vision - ECCV 2018 - 15th European Conference, Munich, Germany, September 8-14, 2018, Proceedings, Part XIII*, volume 11217 of *Lecture Notes in Computer Science*, pages 227–243. Springer, 2018. 2

[45] Zhanpeng Zhang, Ping Luo, Chen Change Loy, and X. Tang. From facial expression recognition to interpersonal relation prediction. *International Journal of Computer Vision*, 126:550–569, 2017. 1, 3, 4

[46] Kaili Zhao, Wen-Sheng Chu, and Honggang Zhang. Deep region and multi-label learning for facial action unit detection. In *2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016*, pages 3391–3399. IEEE Computer Society, 2016. 2

[47] R. Zhi, M. Flierl, Q. Ruan, and W. B. Kleijn. Graph-preserving sparse nonnegative matrix factorization with application to facial expression recognition. *IEEE Trans Syst Man Cybern B Cybern*, 41(1):38–52, 2011. 2