https://doi.org/10.20965/jaciii.2019.p0883

Paper:

Emotion Recognition Based on Multi-Composition Deep Forest and Transferred Convolutional Neural Network

Xiaobo Liu*,, Xu Yin*,**, Min Wang*,**, Yaoming Cai***, and Guang Qi***

*School of Automation, China University of Geosciences
388 Lumo Road, Wuhan, Hubei 430074, China
E-mail: xy@cug.edu.cn
**Hubei Key Laboratory of Advanced Control and Intelligent Automation for Complex Systems
388 Lumo Road, Wuhan, Hubei 430074, China
***School of Computer Science, China University of Geosciences
388 Lumo Road, Wuhan, Hubei 430074, China

[Received October 13, 2018; accepted April 4, 2019]

In human-machine interaction, facial emotion recognition plays an important role in recognizing the psychological state of humans. In this study, we propose a novel emotion recognition framework based on using a knowledge transfer approach to capture features and employ an improved deep forest model to determine the final emotion types. The structure of a very deep convolutional network is learned from ImageNet and is utilized to extract face and emotion features from other data sets, solving the problem of insufficiently labeled samples. Then, these features are input into a classifier called multi-composition deep forest, which consists of 16 types of forests for facial emotion recognition, to enhance the diversity of the framework. The proposed method does not need require to train a network with a complex structure, and the decision tree-based classifier can achieve accurate results with very few parameters, making it easier to implement, train, and apply in practice. Moreover, the classifier can adaptively decide its model complexity without iteratively updating parameters. The experimental results for two emotion recognition problems demonstrate the superiority of the proposed method over several well-known methods in facial emotion recognition.

Keywords: emotion recognition, transfer learning, convolutional neural network, multi-composition deep forest

1. Introduction

Human facial expression is an indispensable method of communication; psychological states can be explored to fully understand the intentions of people by studying their emotional appearance [1]. With the development of human-machine interaction (HMI) and artificial intelligence, the ability to express and recognize human emotions is becoming increasingly imperative for computers [2]. In terms of smart interaction and emotional computing technology, emotion recognition is a perceptual measure for information exchange and has extensive research potential in many areas, such as in patient sentiment analysis, brain-computer interfaces, and blind vision [3].

Emotion recognition mainly includes two parts: feature extraction of facial emotion and emotion classification [4]. To extract emotion features, Niu et al. [5] combined a Gabor wavelet with a histogram of gradient (HOG) to extract multi-scale and multi-directional features from relevant regions; Jia et al. [6] proposed an extraction method based on a combination of sparse representation and local binary pattern (LBP) histogram features. These solved the problem of image noise and low resolution and enhanced the expression ability of human countenance texture features. However, these traditional methods are unhelpful for extracting deeper and/or nonlinear features to further enhance the effects of representation learning. Convolutional neural networks (CNNs) have powerful self-learning and abstract expression capabilities and have been applied extensively in image processing. Byeon and Kwak [7] utilized a 3D CNN to extract expression features; the extracted features had a strong identification potential for improving classification accuracy. In recent years, CNNs have been designed for deeper and more complex structures, such as AlexNet, GoogLeNet, and the very deep convolutional network proposed by the Visual Geometry Group (VGG) of the Department of Engineering Science at the University of Oxford [8]. "VGG16" adopts 16 network layers, and the effect of feature extraction is significantly enhanced. However, using a deep neural network (DNN) to extract features also presents certain difficulties such as the dependence of labeled samples on certain quantities, a time-consuming training process, and the need for expensive calculating facilities [9]. To resolve these difficulties, a transfer learning method is widely used, between different but similar domains [10]. This method not only solves the issue of a lack of training samples but also transfers well-trained models among different tasks and reduces time consumption owing to repeated training [11].

With regard to emotion classification, Michel and

Kaliouby [12] used a support vector machine (SVM) and explored its role in terms of HMI. Murugappan [13] presented a classification of human emotions using electroencephalogram (EEG) signals, and the validation of statistical features was performed using 5-fold cross validation; further, a nonlinear classifier was used. Wang and Liu [14] adopted a backpropagation neural network (BPNN) for face monitoring and classification and achieved rapid and effective results. However, these algorithms require complex artificial adjustments to fit a large number of hyperparameters and can cause the overfitting phenomenon to occur when there is a lack of sufficient training samples [15]. Deep forest is a deep ensemble model proposed by Zhou and Feng [16]. It is composed of decision trees with clear classification rules. The number of layers in deep forest is determined automatically by cross-validation, effectively alleviating the overfitting problem. Fewer parameters make this model more robust, and the ensemble structure makes the deep forest insensitive to adjusting hyperparameters [17].

In this paper, an emotion recognition framework is proposed. Emotion features are extracted by transferring from the VGG16 model; they are then classified by a multi-composition deep forest (MCDF) model composed of 16 types of forests, which increases the ensemble diversity of the model. The remainder of this paper is structured as follows. Section 2 describes the basic algorithms regarding VGG16 and deep forest. Section 3 presents the overall framework for emotion recognition. Section 4 presents experimental settings and results. Section 5 draws conclusions and presents an outlook for this study.

2. Basic Algorithms

In this section, the very deep convolutional network model VGG16 is introduced, and a detailed theory regarding deep forest is illustrated.

2.1. Very Deep Convolutional Network

CNNs generally include convolutional layers, pooling layers, and fully connected layers. Convolution kernels are contained in convolutional layers whose parameters are trainable, and the core of the training process involves updating these parameters [18]. As illustrated in **Fig. 1**, VGG16 is composed of 13 convolutional layers and 3 fully-connected layers. Blocks with two or three convolution layers are divided, and then a max-pooling layer is utilized to decrease the size of the input and maintain the invariance for network translation. In this regard, 3×3 convolution kernels are adopted for each layer in VGG16 and can obtain more activation functions, richer features, and stronger discriminating abilities [19].

2.2. Deep Forest

Deep forest is different from traditional neural networks; it is a non-differential module-based model composed of decision trees [16]. As in shown in **Fig. 2**, each layer of deep forest consists of random forests and completely-random tree forests (C-RTFs). Each decision tree in the random forest randomly selects $\sqrt{d}$ (d is the number of input features) features in the entire feature space as candidates, and then chooses the feature with best *Gini* value as a split node to grow. Each tree in C-RTF is generated by randomly selecting one feature in the entire feature space as a split feature of the node [20]. Both the random forest and the C-RTF consist of multiple decision trees. The class probability values generated by all decision trees are averaged, and the category corresponding to the maximum value is taken as the final decision category. In the deep forest, only the class probability vectors are utilized. The representation features are connected by the class probability values of all forest outputs from the previous layer and are connected to the original features as the input of the next layer. The number of layers is determined by cross-validation, and the fewer hyperparameters contained in the deep forest do not need many "tricks" for adjustment, avoiding the risk of overfitting and increasing the robustness of its structure.

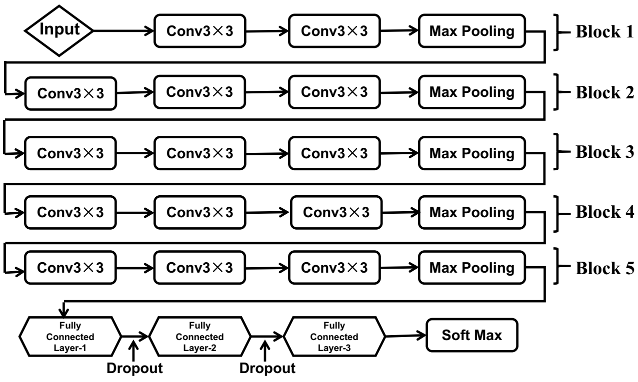

Fig. 1. The composition and construction of VGG16.

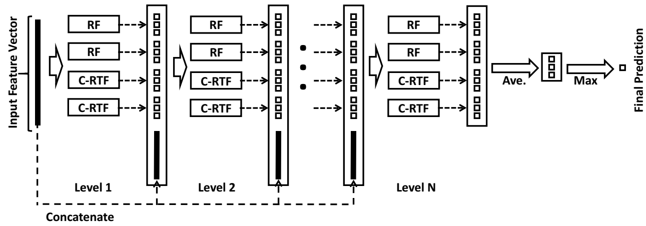

Fig. 2. The structure of deep forest and the connection of class vectors.

3. The Proposed Emotion Recognition Framework

The proposed framework captures features by transferring the VGG16 model from the ImageNet dataset (source domain) and classifies sample features by MCDF. The overall architecture is shown in **Fig. 3**, where the train-

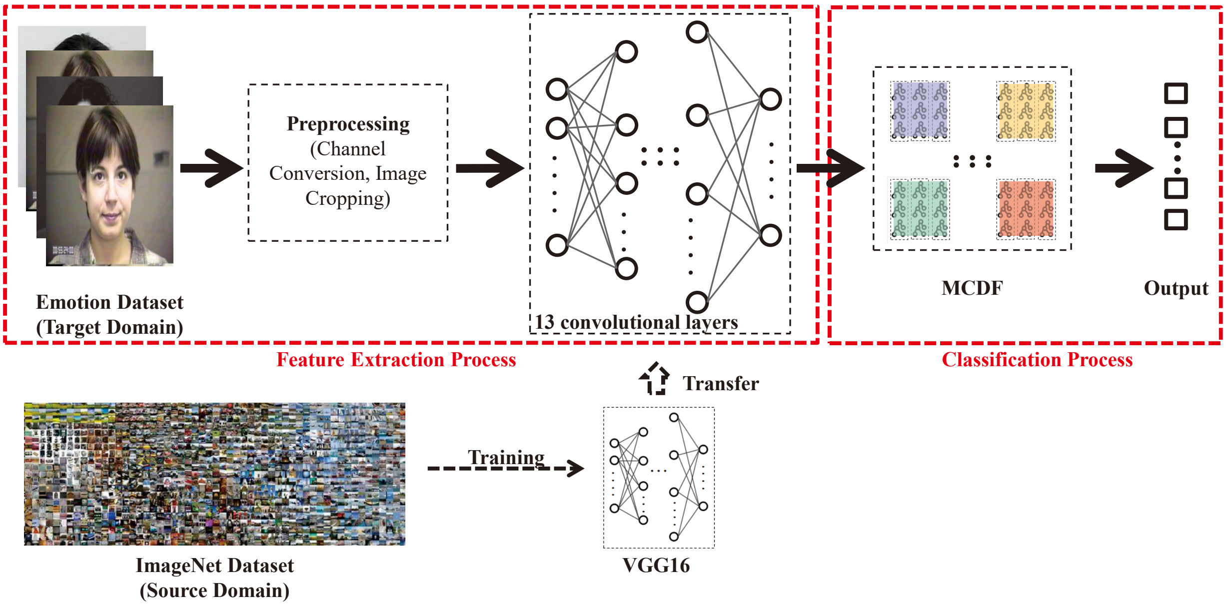

Fig. 3. The overall architecture for emotion recognition.

ing process on the source domain represents the source of the trained model. Thus, this study utilizes an available model that is already trained, abandoning the need to repetitively perform a training process for a specific task.

In the proposed framework, original images are first preprocessed and divided into uniform sizes centered on the middle pixel, to ensure that the edges, rather than the important emotion features, of the image are clipped. As VGG16 is set with three input channels for each image, all emotion images are converted into three channels in vector form. Secondly, the trained model is directly transferred, to extract emotion features. VGG16-IN is a universal DNN already trained on the ImageNet dataset, and can recognize more than 22,000 objects. More than 15 million labeled images are contained for these objects in the ImageNet dataset. The category "Human" is contained in the ImageNet dataset, where facial features are related to emotion features. Regarding ImageNet as the source domain and transferring VGG16-IN to the target domain to carry out tasks will save substantial training time and reduce the high requirements on the number of training samples and computing facilities. In that regard, the last 3 layers in VGG16-IN are fully-connected layers. Therefore, this study only utilized 13 convolutional layers on emotion data, without retraining.

Finally, a supervised method is performed to classify the emotion samples by the MCDF model. Training data, test data, and validation data are divided to create the training model, achieve testing accuracy, and assess the performance of deep forest architecture. Here, MCDF is modified by adopting fewer decision trees and more forest species. The diversity of an individual learner will lead to "disagreement" and using different parameter settings of the base learning algorithm for generating diverse individual learners is an effective way to enhance diversity. Roughly speaking, a variety of different weak classifiers will contribute to the correctness of the decision. Consequently, increasing the diversity can improve the performance of the ensemble learner. For deep forest, the rules that integrate several weak classifiers and determine output by voting can reduce the influence of changing parameters. Moreover, the proposed classifier prefers to set fewer decision trees in each forest to simplify the structure and save training time. The smallest component of the MCDF is a decision tree, and the acceptable input is in the form of a one-dimensional vector. Thus, the final layer of the convolutional network outputs the features; these are stretched into a one-dimensional vector form and are used as the input features of the MCDF for subsequent operations.

Figure 4 shows the composition of each layer in the deep forest. A total of 16 forests are realized using 4 different criteria; **Table 1** explains the meanings and functions of setting these 4 criteria. Samples are processed in the form of vectors in the MCDF. The input of each layer is feature vectors, and the output of each layer is class vectors. The output of the deep forest is a set of prediction categories with the same number of input batches. Under the premise of having little impact on accuracy, this study explored the concept that 100 decision trees in each forest can obtain a better performance in data sets of different sizes and types.

4. Experiments

This study evaluates the proposed method by facial emotion datasets. In this section, the descriptions of datasets, experimental settings, comparison algorithms, experimental results, and analysis are construed.

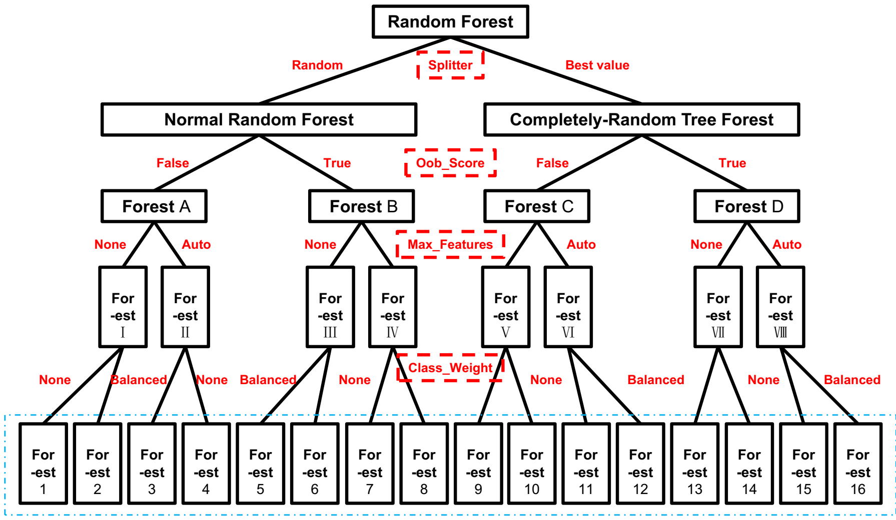

Fig. 4. The composition of each layer in the deep forest, and the approach we select for various forests; "Forest1," "Forest2," . . . , "Forest16" are the 16 types of forest that this study adopts in the deep forest algorithm.

Table 1. The meanings and functions of setting criterions.

Criterion	Meanings and functions
Splitter	The method of selecting a split feature, which is closely related to the bifurcation trend for each tree.
Oob_Score	The samples outside the bag to assess the model quality, affecting the generalization ability.
Max_Features	The maximum number of features that should be considered; this also may affect the phenomenon of overfitting.
Class_Weight	Adjusting the weights of category distribution could weaken the bias of voting for ensemble classifiers.

4.1. Description of Dataset

Two datasets are utilized for evaluating the proposed framework, and one of the emotion datasets is CK+ data,[1] which was extended from CK and published in 2010. The data set contains 123 subjects and 593 image sequences, in which 327 images with labels are divided into 7 categories (0-Angry, 1-Despised, 2-Disgusted, 3-Fear, 4-Happy, 5-Sad, and 6-Surprised). More descriptions and application cases for the CK+ dataset are detailed in [21]. The other dataset is Jaffe data,[2] including 213 photos with 256×256 pixels. The 7 categories of expressions (0-Neutral, 1-Happy, 2-Sorrowful, 3-Surprised, 4-Angry, 5-Disgusted, and 6-Scary) are photographed in 10 females. **Fig. 5** displays several examples from the two datasets.

Fig. 5. The presentation of different expressions in two datasets. Among them, the first row is 7 categories in the Cohn-Kanade+ (CK+) dataset, and the second row is 7 categories in the Jaffe dataset.

4.2. Experiment Settings and Comparison Algorithms

In the experiments, images are cropped into 225×225 sizes, and 5-fold cross-validation is adopted to determine the number of layers for the MCDF and deep forest. To prove the superiority of MCDF for emotion recognition, the SVM, random forest, and C-RTF are performed for emotion classification. Deep neural network-rectified linear unit (DNN-ReLU) employs 3 fully connected neural networks and adopts the rectified linear unit (ReLU) as the activation function. Random forest applies 300 random trees to classify HSI data, and similarly, C-RTF applies 300 completely-random trees for training and predicting. SVM is a discriminant classifier defined by a classification hyperplane, and the kernel function adopts a radial basis function (RBF).

To reflect the improvement of deep forest caused by increasing the category of forests, a deep forest with a primitive structure is adopted for comparative experiments. The deep forest utilizes 2 random forests and 2 C-RTFs to construct each layer, and each forest contains 500 decision trees. To prove that the transfer of VGG16 is help-

1. http://www.consortium.ri.cmu.edu/ckagree/
2. http://www.kasrl.org/jaffe.html/

Table 2. Comparison of classification results between different classifiers on CK+ dataset.

CK+ Dataset	DNN-ReLU	SVM-RBF	Random Forest	C-RTF	Deep Forest	MCDF
OA [%]	75.40±0.71	59.08±1.21	74.43±0.85	69.61±2.40	76.69±2.01	**77.96±0.69**
AA [%]	77.53±0.43	65.99±2.09	76.20±0.55	72.73±1.87	77.17±3.35	**78.90±0.94**
Angry	69.22±0.15	62.49±0.89	73.89±1.21	73.58±1.25	**82.83±4.23**	69.61±1.29
Despised	78.29±0.38	70.10±1.17	79.88±0.54	76.42±3.73	**85.49±0.65**	68.33±1.38
Disgusted	79.38±0.64	63.83±3.61	**81.21±0.73**	68.33±0.33	80.15±4.22	69.42±1.27
Fear	82.34±0.27	72.52±2.87	67.34±0.29	71.28±1.87	52.23±4.87	**83.15±0.54**
Happy	66.64±0.69	60.35±1.93	79.63±0.86	69.35±3.54	79.65±3.35	**89.21±1.17**
Sad	**82.03±0.34**	59.27±2.45	72.60±0.10	75.29±0.37	76.52±3.34	75.48±0.63
Surprised	**84.81±0.54**	73.37±1.71	78.85±0.12	74.86±1.98	84.32±2.70	81.20±0.33

Table 3. Comparison of classification results between different classifiers on Jaffe dataset.

Jaffe Dataset	DNN-ReLU	SVM-RBF	Random Forest	C-RTF	Deep Forest	MCDF
OA [%]	70.38±1.39	64.36±0.93	71.15±1.24	70.02±0.39	72.23±2.68	**73.81±1.36**
AA [%]	73.69±2.27	67.26±1.35	71.98±2.01	71.11±0.52	72.79±2.99	**74.90±1.42**
Neutral	72.15±3.38	73.85±2.04	**77.36±1.29**	70.60±0.83	73.53±2.21	75.46±1.38
Happy	80.02±0.75	66.14±0.79	78.37±0.73	68.52±0.15	68.35±2.39	**82.13±2.20**
Sorrowful	79.63±2.68	72.48±3.22	59.65±3.68	73.29±0.80	59.93±3.70	**85.29±1.95**
Surprised	68.43±2.33	70.39±0.98	68.36±2.01	76.35±0.34	82.09±1.93	**82.11±1.06**
Angry	71.26±1.19	58.27±0.35	71.38±1.85	62.39±0.54	**73.21±3.65**	71.05±0.79
Disgusted	74.35±2.07	68.73±0.96	74.99±2.77	**75.90±0.67**	67.10±3.86	68.93±1.21
Scary	69.99±3.49	60.96±1.11	73.75±1.74	70.72±0.31	**75.32±3.19**	59.38±1.33

ful for classifying emotion samples, an MCDF classifier without feature extraction by VGG16-IN is carried out in the experiments, and the input of the MCDF is a preprocessed image vector.

The values of experimental results are averaged after 10 epochs, and this study utilizes 40% data for training a classifier, 50% data for testing, and 10% data for validating. The number of samples in the two sentiment data sets is limited, but the sample ratio is sufficient to train the model of the proposed algorithm and the comparison algorithms. The use of validating data can prevent overfitting and improve the classification performance for emotion classification tasks.

The experiments use a personal computer with an Intel-i5 3.20 GHz CPU and 2 GB RAM, and the operating system is Linux. The programming language is implemented in Python. In the image preprocessing procedure, image cropping and channel converting use the OpenCV framework, and a TensorFlow framework is implemented in the MCDF construction procedure.

4.3. Experimental Results and Analysis

The evaluation standards for the experiments are overall accuracy (OA) and average accuracy (AA). OA reflects the classification accuracy of all samples, and AA reflects the classification accuracy of various samples. The formulas are as follows:

$$OA = \frac{N_R}{N_A} \quad (1)$$

$$AA = \frac{\sum_{i=1}^{n} A_{Ci}}{n} \quad (2)$$

In the above, N_A represents the number of all training samples, and N_R represents the number of samples correctly identified by the classifier. n represents the number of categories, and A_{Ci} represents the classification accuracy of the i-th category.

The experimental accuracies on the CK+ dataset are shown in **Tables 2** and **3** shows the experimental results on the Jaffe dataset. To prove the effects of feature extraction, **Fig. 6** shows the accuracy curves after abandoning the process of feature extraction by VGG16-IN. At the same time, these curves illustrate the effects of changes in the number of decision trees on accuracy.

For different classifiers, **Tables 2** and **3** have similar classification effects on the CK+ dataset and Jaffe dataset. The results indicate that MCDF possesses better performance than the other 5 algorithms, and that the proposed algorithm can distinguish facial emotion with high accuracy. Moreover, as compared with the original deep forest, MCDF can improve the accuracy by 1.32% on the CK+ dataset, and by 1.63% on the Jaffe dataset. This demonstrates that increasing the diversity for the ensemble model can achieve better performance and proves the effectiveness of improving the deep forest model. Other classifiers show poor accuracy on the two datasets, even less than the accuracy of the deep forest model without improvement.

In the classification evaluation for the proposed method, the confusion matrices for the proposed algorithm are shown in **Fig. 7**. The left confusion matrix is the result of the classification results on the CK+ dataset, and the right is the result on the Jaffe dataset. In the confusion matrices, the x-axis represents the predicted labels, and the y-axis represents the true labels. To clearly show the details of the classification, the accuracy of each category is given in the table. It is found that as compared with other algorithms, the proposed method achieves the highest classification accuracy in several categories, on both datasets.

The curves in **Fig. 6** indicate that utilizing the VGG16 transferred from ImageNet dataset is helpful for classifying emotion samples. On the two datasets, the OA curves and AA curves display similar performance, illustrating that classifying by MCDF with feature extraction by VGG16-IN has better classification results. In addition, by observing the influence of changing the number of decision trees on the accuracy, it can be summarized that the accuracy changes are very small or even nonevident trends whether or not the feature extraction process is performed. It is also found that MCDF is more robust for classifying the extracted features.

5. Conclusion and Outlook

In this paper, a novel emotion recognition framework is proposed. First, input images are preprocessed by cropping pictures and transforming channels. Second, a deep CNN is utilized by transferring data from the source domain to capture the emotion features. Finally, an improved deep forest is employed for emotion classification, and this study increased the composition of species of the deep forest, to enhance the capability of the ensemble model. From experiments on two emotion datasets, this study certified the superiority of the proposed framework and also certified that applying VGG16-IN to extract emotion features without repeated training has a positive impact on classification. In future work, we will consider transferring the deep forest model, for robust performance.

Acknowledgements

This work is partially supported in part by the National Nature Science Foundation of China (Grant No. 61603355 and 61773355), National Nature Science Foundation of Hubei Province, China (Grant No. 2018CFB528), the Fundamental Research Funds for National University, China University of Geosciences (Wuhan) under grant No. G1323541717.

References:

[1] M. E. Ayadi, M. S. Kamel, and F. Karray, "Survey on speech emotion recognition: features, classification schemes, and databases," Pattern Recogn., Vol.44, No.3, pp. 572-587, 2011.

[2] D. H. Kim, M. K. Lee, D. Y. Choi, and B. C. Song, "Multi-modal emotion recognition using semi-supervised learning and multiple neural networks in the wild," Proc. of the 19th ACM Int. Conf. on Multimodal Interaction, pp. 529-535, 2017.

[3] C. Busso, Z. Deng, S. Yildirim, M. Bulut, et al., "Analysis of emotion recognition using facial expressions, speech and multimodal information," ACM Int. Conf. on Multimodal Interface, No.4, pp. 205-211, 2004.

[4] S. E. Kahou, X. Bouthillier, P. Lamblin, et al., "Emonets: Multimodal deep learning approaches for emotion recognition in video," J. on Multimodal User Interfaces, Vol.10, No.2, pp. 99-111, 2016.

[5] L. Q. Niu, Z. T. Zhao, and S. N. Zhang, "Extraction method for facial expression features based on gabor feature fusion and LBP histogram," J. of Shenyang Univ. of Technol., Vol.38, No.1, pp. 63-68, 2016. (In Chinese)

[6] Q. Jia, X. Gao, H. Guo, et al., "Multi-layer sparse representation for weighted LBP-patches based facial expression recognition," Sensors, Vol.15, No.3, pp. 6719-6739, 2015.

[7] Y. H. Byeon and K. C. Kwak, "Facial expression recognition using 3D convolutional neural network," Int. J. of Adv. Comp. Science and Appl., Vol.5, No.12, pp. 107-112, 2014.

[8] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," arXiv preprint, arXiv:1409.1556, 2014.

[9] W. Samek, A. Binder, G. Mintavon, S. Lapuschkin, and K. R. Muller, "Evaluating the visualization of what a deep neural network has learned," IEEE Trans. on Neural Networks and Learning Systems, No.99, pp. 1-14, 2016.

[10] H. W. Ng, V. D. Nguyen, V. Vonliikakis, and S. Winkler, "Deep learning for emotion recognition on small datasets using transfer learning," Proc. ACM Int. Conf. on Multimodal Interaction, pp. 443-449, 2018.

[11] Y. Bengio. "Deep learning of representations for unsupervised and transfer learning," Workshop on Unsupervised and Transfer Learning, No.7, pp. 1-20, 2012.

[12] P. Michel and R. Kaliouby, "Real time facial expression recognition in video using support vector machines," Proc. ACM Int. Conf. on Multimodal Interaction, pp. 258-264, 2003.

[13] M. Murugappan, "Human emotion classification using wavelet transform and KNN," Int. Conf. on Pattern Anal. and Intelli. Rob., No.1, pp. 148-153, 2011.

[14] J. Wang and B. Liu, "A study on emotion classification of image based on BP neural network," Inf. Science and Manage. Eng., No.1 pp. 100-104, 2010.

[15] Y. J. An, S. T. Sun, and S. J. Wang, "Naive bayes classifiers for music rmotion classification based on lyrics," IEEE/ACIS Int. Conf. on Comp. and Inf. Science, 2017.

[16] Z. H. Zhou and J. Feng, "Deep forest: towards an alternative to deep neural networks," 26th Int. Joint Conf. on Artifical Intelli., pp. 3553-3559, 2017.

[17] Y. Guo, S. Liu, Z. Li, and X. Shang, "BCDForest: a boosting cascade deep forest model towards the classification of cancer subtypes based on gene expression data," Bmc Bioinf., Vol.19, No.5, pp. 118, 2018.

[18] H. C. Shin, H. R. Roth, M. Gao, L. Lu, et al., "Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning," IEEE Trans. on Med. Imaging, Vol.35, No.5, pp. 1285, 2018.

[19] A. Sengupta, Y. Ye, R. Wang, C. Liu, and K. Roy, "Going deeper in spiking neural networks: VGG and residual architectures," Comp. Vision and Pattern Recognit., 2018.

[20] T. Wu, Y. H. Zhao, L. F. Liu, H. X. Li, et al., "A novel hierarchical regression approach for human facial age estimation based on deep forest," IEEE Instrum. Meas. Technol. Conf., pp. 1-6, 2018.

[21] P. Lucey, J. F. Cohn, T. Kanade, J. Saragih, et al., "The extended cohn-kanade dataset (CK+): a complete dataset for action unit and emotion-specified expression," Comp. Vision and Pattern Recognit. Workshops, Vol.36, No.1, pp. 94-101, 2010.

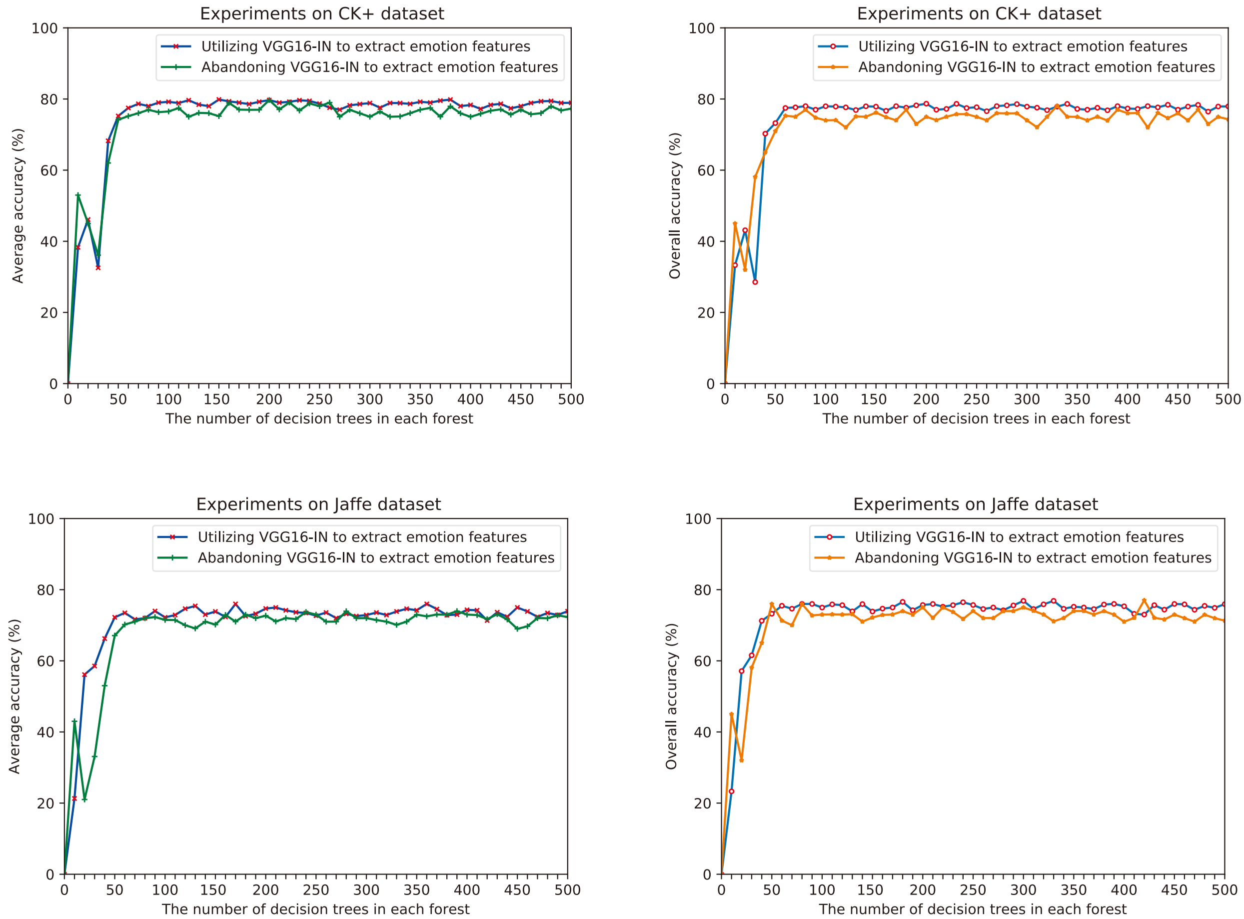

Fig. 6. Comparison curves for feature extraction by VGG16-IN and without feature extraction on two datasets.

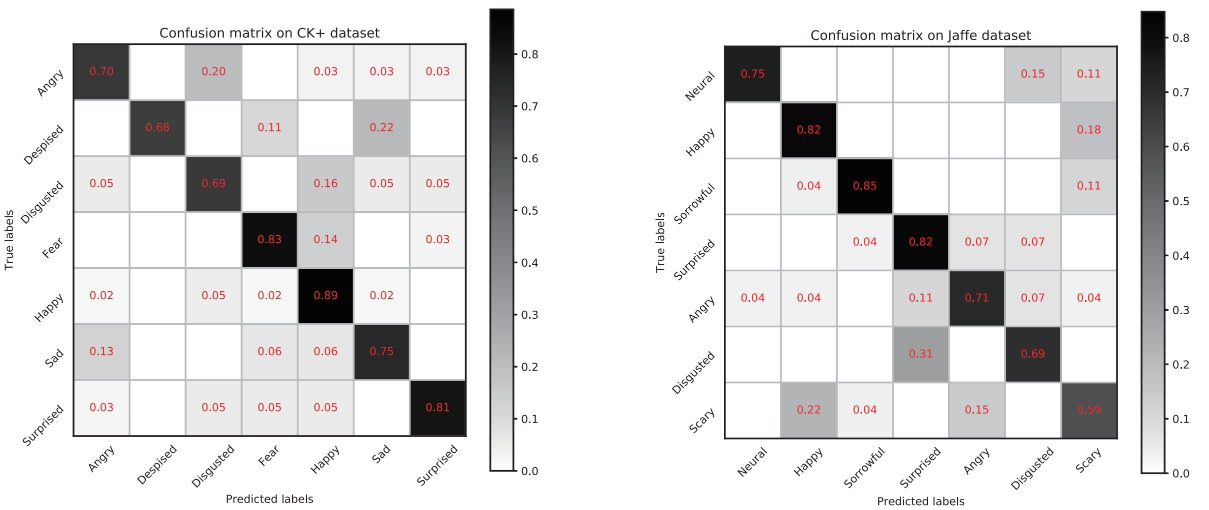

Fig. 7. Confusion matrices of the proposed method.

Name:
Xiaobo Liu

Affiliation:
School of Automation, China University of Geosciences

Address:
388 Lumo Road, Wuhan, Hubei 430074, China
Brief Biographical History:
2005- B.E. in School of Computer Science, China University of Geosciences
2009- Ph.D. in School of Computer Science, China University of Geosciences
2010- Visiting Student in Faculty of Computer Science, University of New Brunswick
2012- Lecturer, China University of Geosciences
2018- Associate Professor, China University of Geosciences
Main Works:
• "Hierarchical Ensemble of Extreme Learning Machine," Pattern Recognit. Letters, DOI: 10.1016/j.patrec.2018.06.015, 2018.
• "Ensemble Transfer Learning Algorithm," IEEE ACCESS, Vol.6, No.99, pp. 2389-2396, 2018.

Name:
Xu Yin

Affiliation:
School of Automation, China University of Geosciences

Address:
388 Lumo Road, Wuhan, Hubei 430074, China
Brief Biographical History:
2017- B.E. in School of Automation, China University of Geosciences
Main Works:
• "Deep Forest-Based Classification of Hyperspectral Images," The 37th Chinese Control Conf., pp. 10367-10372, 2018.

Name:
Min Wang

Affiliation:
School of Automation, China University of Geosciences

Address:
388 Lumo Road, Wuhan, Hubei 430074, China
Brief Biographical History:
2018- B.E. in School of Automation, China University of Geosciences

Name:
Yaoming Cai

Affiliation:
School of Computer Science, China University of Geosciences

Address:
388 Lumo Road, Wuhan, Hubei 430074, China
Brief Biographical History:
2016- B.E. in School of Computer Science, China University of Geosciences
2018- Ph.D. in School of Computer Science, China University of Geosciences
Main Works:
• "Extreme Learning Machine Based On Evolutionary Multi-Objective Optimization," The 12th Int. Conf. on Bio-inspired Computing: Theor. and Appl., pp. 420-435, 2017.

Name:
Guang Qi

Affiliation:
School of Automation, China University of Geosciences

Address:
388 Lumo Road, Wuhan, Hubei 430074, China
Brief Biographical History:
2005- B.E. in School of Earth Resources, China University of Geosciences
2011- Ph.D. in School of Computer Science, China University of Geosciences
2012- Lecturer, China University of Geosciences
Main Works:
• Geographic information system, 3D modeling, and image processing