



# Teeth Category Classification by Fractional Fourier Entropy and Improved Hybrid Genetic Algorithm

Siyuan Lu<sup>1,2(✉)</sup> and Liam O'Donnell<sup>3</sup>

<sup>1</sup> Guangxi Key Laboratory of Manufacturing System, Advanced Manufacturing Technology, Guilin 541004, Guangxi, China

siyuan\_lu@foxmail.com

<sup>2</sup> School of Informatics, University of Leicester, Leicester LE1 7RH, UK

<sup>3</sup> School of Engineering, University of Limerick, Limerick, Ireland

**Abstract.** It is significant to classify teeth categories in dental treatment. A novel teeth classification method was proposed in this paper, which combined fractional Fourier entropy and feedforward neural network. Firstly, fractional Fourier transform was performed on the teeth CT images and the obtained spectrums were used to extract entropies as the features. Then, a feedforward neural network was employed for automatic classification. To train the parameters in the network, improved hybrid genetic algorithm was leveraged. Experiment results suggested that our method achieved state-of-the-art performance.

**Keywords:** Teeth classification · Fractional fourier transform · Entropy · Neural network · Genetic algorithm

## 1 Introduction

Teeth are important for human beings. They help us to chew. Teeth can grind food into small pieces which is the first step of digestion [1]. This decomposition can stimulate the further digestion in stomach. Our communication also depends on teeth. Teeth, tongue and lip must work harmoniously for pronunciation of human language. Meanwhile, teeth are playing a significant role for facial expression. Teeth can serve as weapon in emergent situations, they are the gifts from nature. Generally, there are four kinds of teeth in human, they are incisor, canine, premolar and molar.

Human beings have paid a lot of attention to protecting their teeth, but many still suffer from dental illness [2]. The recognition of teeth category is the first step for diagnosis of dental diseases, which is vital for clinical treatment. Manual classification is weak in reproducibility, so researchers try to develop automatic and accurate teeth classification systems using artificial intelligence.

Mahoor and Abdel-Mottaleb (2005) [3] developed their teeth classification system based on bitewing images. They firstly performed Fourier transform on the images for feature extraction. Then, the obtained feature vectors were fed into a Bayesian classifier for training and testing. The labels of the images were binary, which include molar and premolar. To boost the detection precision of their system, the spatial information was

used as well. There are totally 50 images in their dataset. Their system achieved promising accuracy on experiment. Lu (2018) [4] used principal component analysis (PCA) and extreme learning machine (ELM) to classify four tooth categories. Payne (2018) [5] combined Hu moment invariant (HMI) with extreme learning machine (ELM).

The above teeth classification methods achieved good performance, but the accuracy can be improved. In this paper, we proposed a novel teeth classification method based on fractional Fourier entropy (FRFE) feedforward neural network, and improved hybrid genetic algorithm (IHGA). FRFE was employed for feature extraction and feedforward neural network was the classification algorithm. The parameters in the network were optimized by IHGA. Our approach yielded better classification performance than several state-of-the-art methods.

## 2 Dataset

To evaluate our approach, computed tomography teeth image was used in experiment. There are four categories of samples in the dataset: incisor, canine, premolar and molar, and each category contain 50 samples. Some samples are given in Fig. 1.

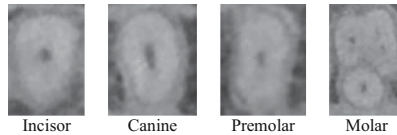


Fig. 1. Teeth images

## 3 Methodology

Image based machine learning systems usually solve two major challenges: feature extraction and classifier training. Feature extraction is to generate some representations from images because images contain too much information. Classifier training is to determine the parameters in classification models to achieve the best accuracy. So, in our scheme, FRFE was leveraged for feature extraction and feedforward neural network was employed for classification. We proposed a novel IHGA for optimization of the parameters in neural network for better generalization ability.

### 3.1 FRFE

Fractional Fourier entropy (FRFE) [6–15] is a combination of fractional Fourier transform (FRFT) and Shannon entropy. It has been successfully applied into many fields. Given a function  $f(x)$ , its  $\alpha$ -angle FRFT can be expressed as [16]:

$$r_z(v) = \int_{-\infty}^{+\infty} G_\alpha(x, v) f(x) dx \quad (1)$$

where  $x$  represents the time and  $v$  the frequency. The definition of transform kernel  $G$  is:

$$G_\alpha(x, v) = \sqrt{1 - i \cot \alpha} \times \exp [i\pi(v^2 \cot \alpha - 2vx \cot \alpha + x^2 \cot \alpha)] \quad (2)$$

where  $i$  is the imaginary unit. As teeth images are two dimension signals, the FRFT needs to be extended with two angles:  $\alpha$  and  $\beta$ . The FRFE denoted by  $F$  can be obtained easily after FRFT by entropy operator  $E$ :

$$F = E \cdot r \quad (3)$$

### 3.2 Feedforward Neural Network

Feedforward neural network is a basic structure with all the nodes in adjacent layers linked to each other [17]. Feedforward neural network is widely applied in practical problems because it does not require prior distribution information of the samples [18–22]. The architecture of feedforward neural network is shown in Fig. 2, where  $N_I$ ,  $N_H$  and  $N_O$  denote the numbers of nodes in input, hidden and output layers, respectively.

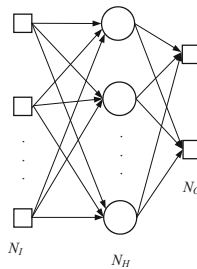


Fig. 2. Feedforward neural network structure

The training of the network is to determine the parameters. Although back propagation is a good choice for training algorithm, it cannot guarantee to converge at the global best solution, because back propagation belongs to a greedy algorithm which depends on gradient descent. Therefore, we try to solve the training problem using optimization methods [23–28].

### 3.3 Standard Genetic Algorithm

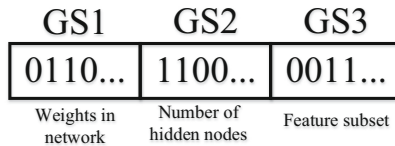
Standard genetic algorithm (GA) belongs to an optimization method, which was inspired by the Darwin's famous evolution theory [29]. GA mimics the behavior of reproduction, crossover and mutation to get the fittest solution.

The solutions are randomly initialized and encoded into strings of '0' and '1' stored in chromosomes. In each generation, the fitness of all the potential solutions will be calculated and sorted. Elitism is used to preserve the high quality solutions, in which several top ranking solutions shall be copied in to the next generation directly. Some solutions will be moved into the next generation by crossover and mutation operations. The stopping criterion for GA can be a pre-defined fitness value or the maximum generation. The top ranking solution in the last generation can be the global best one [30, 31].

However, GA is weak in local searching, and it sometimes cannot converge because the fitness of descendants becomes worse with the generations.

### 3.4 Improved Hybrid Genetic Algorithm

IHGA is proposed by Ahmad, Isa (2013) [32], which not only trains the weights in network but also finds the best number of hidden nodes and feature subset. The chromosome in IHGA is divided into three gene segments (GS) for three purposes, shown in Fig. 3.



**Fig. 3.** Chromosome in IHGA

The fitness of the solutions is defined as:

$$fit = w \times acc + (1 - r) \times \frac{1}{cp} \tag{4}$$

where  $w$  is the weight to compromise between the testing accuracy  $acc$  and the network complexity inverse  $1/cp$ . The definitions of  $acc$  and  $cp$  are given below:

$$acc = 100 \times \left( \frac{N_C}{N_T} \right) \tag{5}$$

$$cp = (f \times h) + (h \times o) + h + o \tag{6}$$

Where  $N_C$  and  $N_T$  denote the number of correctly classified samples and total sample number, respectively. The  $f$ ,  $h$  and  $o$  represent the number of selected features, the hidden nodes number and the output nodes number, respectively.

IHGA employs segmented multi-chromosome crossover (SMCC) to generate offspring chromosome that gets gene from more than one couple parent chromosomes. The diagram of IHGA is summarized in Fig. 4.

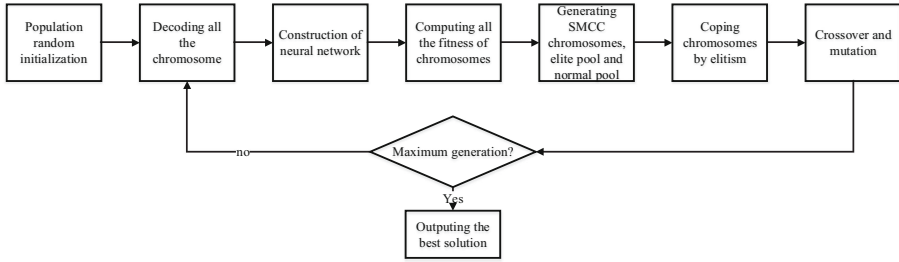


Fig. 4. Steps of IHGA

### 3.5 10-Fold Cross Validation

Cross validation is a method for training. It is often used to prevent overfitting when the dataset is small. The k-fold cross validation divides the dataset into k groups of the same size [33–35]. Then, every time, one group is chosen for testing and the other k-1 groups serve for training [36, 37]. The training will be run for k times and each group will be used for testing. Then, the average performance can be obtained. The 10-fold cross validation is illustrated in Fig. 5.

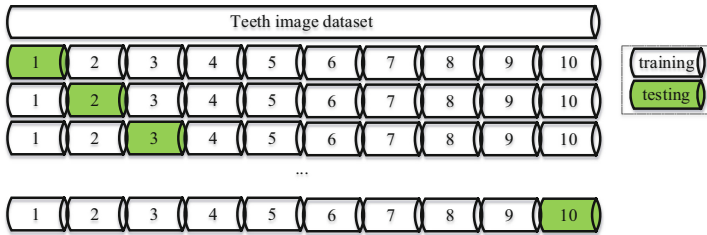
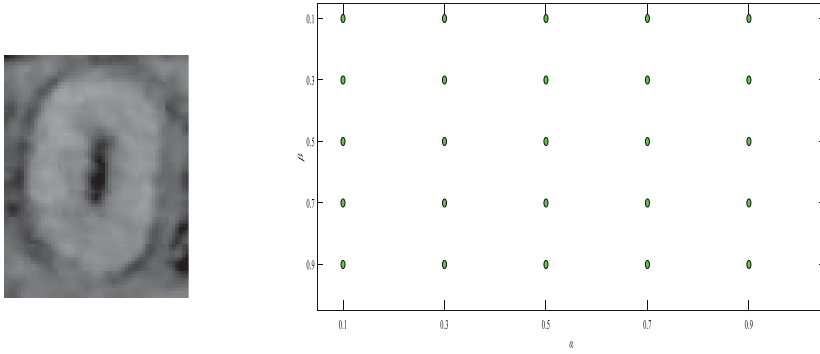


Fig. 5. 10-fold cross validation

## 4 Experiment Results and Discussions

### 4.1 FRFE Results

Here is an example of FRFT. The input was a teeth CT age and 25 pairs of angles were used, shown in Fig. 6. The result of FRFT was given in Fig. 7.



(a) Original input image

(b) angle combination of FRFT

Fig. 6. Input and Parameter of FRFT

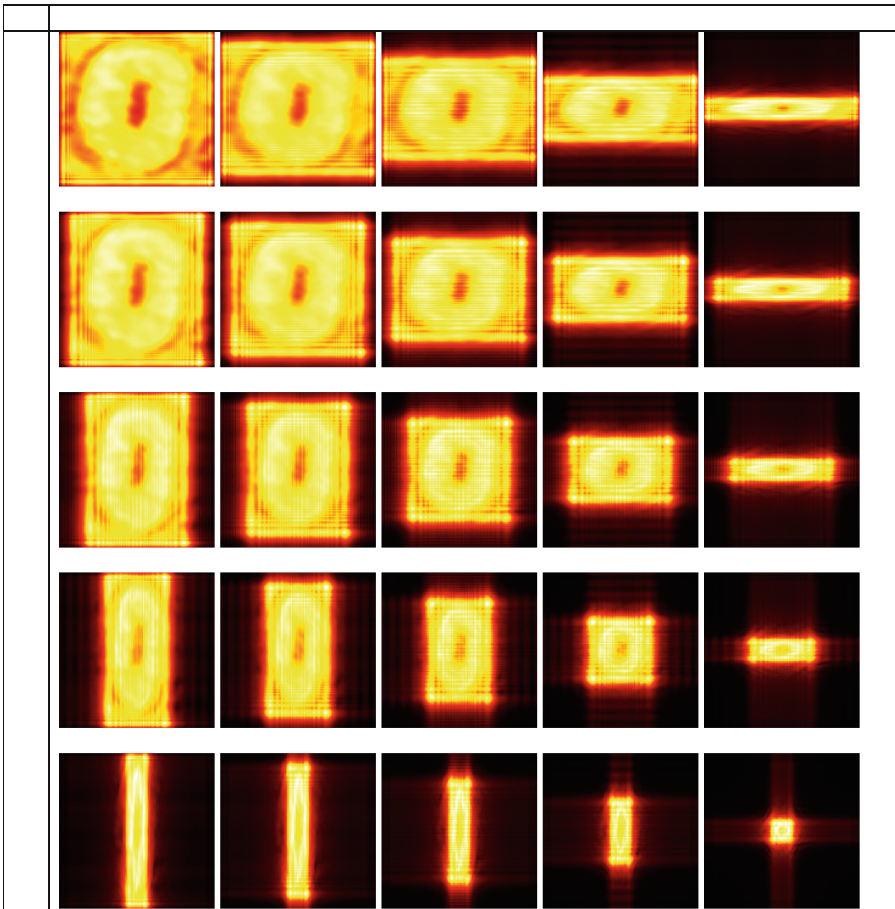


Fig. 7. Results of FRFT

Then, the entropies of the above 25 FRFT spectrums were calculated, shown in Table 1. These 25 FRFEs were fed into the feedforward neural network for training and testing.

**Table 1.** Entropy values of FRFT

6.3632	6.8078	7.2109	7.0521	5.3368
6.8068	7.0813	7.3951	7.1713	5.5611
7.2050	7.3947	7.4329	6.7633	5.6494
6.9844	7.1126	6.7732	5.7245	5.2942
5.2210	5.4708	5.5977	5.3015	4.6309

## 4.2 GA Versus IHGA

The confusion matrixes of our FRFE-IHGA and FRFE-GA were given in Fig. 8 and Fig. 9, respectively. FRFE-IHGA achieved overall accuracy of 80.0% while the accuracy of FRFE-GA was 74.0%. Meanwhile, for sensitivity and specificity of all four classes, FRFE-IHGA outperformed FRFE-GA. So, IHGA was a better option for network parameter optimization than GA in this study.

	C <sub>1</sub>	C <sub>2</sub>	C <sub>3</sub>	C <sub>4</sub>	Sen
C <sub>1</sub>	41	4	5	0	82.0%
C <sub>2</sub>	4	40	4	2	80.0%
C <sub>3</sub>	3	2	40	5	80.0%
C <sub>4</sub>	3	4	4	39	78.0%
Prc	80.4%	80.0%	75.5%	84.8%	Acc 80.0%

**Fig. 8.** Confusion matrix of our FRFE-IHGA

	C <sub>1</sub>	C <sub>2</sub>	C <sub>3</sub>	C <sub>4</sub>	Sen
C <sub>1</sub>	37	6	4	3	74.0%
C <sub>2</sub>	4	38	4	4	76.0%
C <sub>3</sub>	3	4	37	6	74.0%
C <sub>4</sub>	5	4	5	36	72.0%
Prc	75.5%	73.1%	74.0%	73.5%	Acc 74.0%

**Fig. 9.** Confusion matrix if replace IHGA with ordinary GA

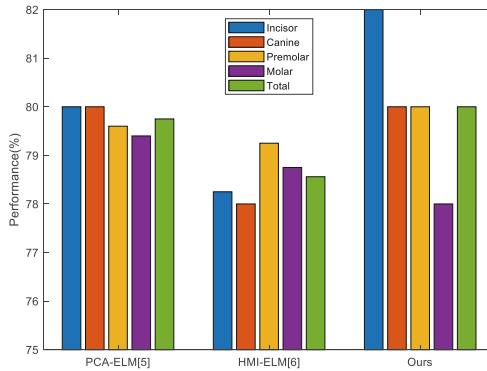
### 4.3 Comparison to State-of-the-Art Approaches

We compared our FRFE-IHGA with two state-of-the-art methods: PCA-ELM [4] and HMI-ELM [5]. As shown in Table 2 and Fig. 10, FRFE-IHGA was better than the other two methods in detecting incisor teeth and premolar teeth. For canine, both FRFE-IHGA and PCA-ELM reached the best sensitivity. Though sensitivity for molar teeth of our method was lower than PCA-ELM, FRFE-IHGA achieved the best overall accuracy of the three approaches. Therefore, our FRFE-IHGA is a good solution for automatic teeth classification.

**Table 2.** Comparison with state-of-the-art approaches

Approach	Incisor	Canine	Premolar	Molar	Total
PCA-ELM [4]	80.00	<b>80.00</b>	79.60	<b>79.40</b>	79.75
HMI-ELM [5]	78.25	78.00	79.25	78.75	78.56
FRFE-IHGA (Ours)	<b>82.0</b>	<b>80.0</b>	<b>80.0</b>	78.0	<b>80.0</b>

(bold means the best)



**Fig. 10.** Comparison against PCA-ELM and HMI-ELM

## 5 Conclusions

In this paper, a new teeth classification method was proposed based on teeth CT images. Fractional Fourier entropy was employed to generate features from images, and a feedforward neural network trained by improved hybrid genetic algorithm served as the classifier. 10-fold cross validation was employed to avoid overfitting. Our method yielded overall accuracy of 80.0%, which was comparable to state-of-the-art methods.

For future research, we shall collect more teeth images and build bigger dataset to re-test our method. We will try to introduce deep learning to improve the classification accuracy.

**Acknowledgement.** This paper is supported by Open Fund of Guangxi Key Laboratory of Manufacturing System & Advanced Manufacturing Technology (17-259-05-011K).

## References

1. Dodds, M.W.J., et al.: An induced extrinsic tooth stain prevention model to investigate whitening potential of sugar-free chewing gums. *Am. J. Dentistry* **30**(6), 309–315 (2017)
2. Vasconcelos, A.G., et al.: Mammal tooth traces in a ferruginous cave in southeastern Brazil and their relevance to cave legal protection. *Anais Da Academia Brasileira De Ciencias*, **91**, 11 (2019). Article ID. UNSP e20180861
3. Mahoor, M.H., et al.: Classification and numbering of teeth in dental bitewing images. *Pattern Recogn.* **38**(4), 577–586 (2005)
4. Lu, S.: Teeth classification based on extreme learning machine. In: *World Conference on Smart Trends in Systems, Security & Sustainability (WS4)*, pp. 198–202. IEEE, London (2018)
5. Payne, R.: Teeth category classification via Hu moment invariant and extreme learning machine. *Adv. Intell. Syst. Res.* **151**, 220–223 (2018)
6. Zhang, Y.-D., Sun, J.: Preliminary study on angiosperm genus classification by weight decay and combination of most abundant color index with fractional Fourier entropy. *Multimedia Tools Appl.* **77**(17), 22671–22688 (2017). <https://doi.org/10.1007/s11042-017-5146-3>
7. Cheng, H.: Multiple sclerosis identification based on fractional Fourier entropy and a modified Jaya algorithm. *Entropy*, **20**(4) (2018). Article ID. 254
8. Li, J.: Texture analysis method based on fractional fourier entropy and fitness-scaling adaptive genetic algorithm for detecting left-sided and right-sided sensorineural hearing loss. *Fundamenta Informaticae* **151**(1–4), 505–521 (2017)
9. Yang, J.F.: Comprehensive survey on fractional fourier transform. *Fundamenta Informaticae* **151**(1–4), 1–48 (2017)
10. Sun, Y.: A Multilayer perceptron based smart pathological brain detection system by fractional fourier entropy. *J. Med. Syst.* **40**(7) (2016). Article ID. 173
11. Li, J., Detection of Left-Sided and Right-Sided Hearing Loss via Fractional Fourier Transform. *Entropy*, 2016. **18**(5): Article ID. 194
12. Cattani, C., et al.: Tea category identification using a novel fractional fourier entropy and jaya algorithm. *Entropy*, **18**(3) (2016). Article ID. 77
13. Liu, G.: Computer-aided diagnosis of abnormal breasts in mammogram images by weighted-type fractional Fourier transform. *Adv. Mech. Eng.* **8**(2) (2016). Article ID. 11
14. Yang, X., et al.: Pathological brain detection by a novel image feature—fractional fourier entropy. *Entropy* **17**(12), 8278–8296 (2015)
15. Chen, S., et al.: Magnetic resonance brain image classification based on weighted-type fractional Fourier transform and nonparallel support vector machine. *Int. J. Imag. Syst. Technol.* **25**(4), 317–327 (2015)
16. Ben Farah, M.A., et al.: A novel chaos based optical image encryption using fractional Fourier transform and DNA sequence operation. *Optics Laser Technol.* **121**, 8 (2020). Article ID. 105777
17. Yavari, M., et al.: Fractional infinite-horizon optimal control problems with a feed forward neural network scheme. *Network-Comput. Neural Syst.* **30**, 23 (2019)
18. Chen, Y.: Cerebral micro-bleeding identification based on a nine-layer convolutional neural network with stochastic pooling. *Concurr. Comput. Pract. Experience* **31**(1), e5130 (2020)
19. Govindaraj, V.V.: High performance multiple sclerosis classification by data augmentation and AlexNet transfer learning model. *J. Med. Imag. Health Inform.* **9**(9), 2012–2021 (2019)
20. Jiang, X.: Chinese sign language fingerspelling recognition via six-layer convolutional neural network with leaky rectified linear units for therapy and rehabilitation. *J. Med. Imag. Health Inform.* **9**(9), 2031–2038 (2019)

21. Ramirez, J.: Unilateral sensorineural hearing loss identification based on double-density dual-tree complex wavelet transform and multinomial logistic regression. *Integr. Comput. Aided Eng.* (2019). <https://doi.org/10.3233/ICA-190605>
22. Li, Z.: Teeth category classification via seven-layer deep convolutional neural network with max pooling and global average pooling. *Int. J. Imag. Syst. Technol.* (2019). <https://doi.org/10.1002/ima.22337>
23. Hong, J., Cheng, H., Zhang, Y.-D., Liu, J.: Detecting cerebral microbleeds with transfer learning. *Mach. Vis. Appl.* **30**(17), 1123–1133 (2019). <https://doi.org/10.1007/s00138-019-01029-5>
24. Xie, S.: Alcoholism identification based on an AlexNet transfer learning model. *Front. Psychiatry*, **10** (2019). Article ID. 205
25. Tang, C.: Cerebral micro-bleeding detection based on densely connected neural network. *Front. Neurosci.* **13** (2019). Article ID. 422
26. Jia, W., Muhammad, K., Wang, S.-H., Zhang, Y.-D.: Five-category classification of pathological brain images based on deep stacked sparse autoencoder. *Multimedia Tools Appl.* **78**(4), 4045–4064 (2017). <https://doi.org/10.1007/s11042-017-5174-z>
27. Zhang, Y.-D., et al.: Image based fruit category classification by 13-layer deep convolutional neural network and data augmentation. *Multimedia Tools Appl.* **78**(3), 3613–3632 (2017). <https://doi.org/10.1007/s11042-017-5243-3>
28. Wang, S.-H., Muhammad, K., Hong, J., Sangaiah, A.K., Zhang, Y.-D.: Alcoholism identification via convolutional neural network based on parametric ReLU, dropout, and batch normalization. *Neural Comput. Appl.* **32**(3), 665–680 (2018). <https://doi.org/10.1007/s00521-018-3924-0>
29. Cappelletti, M.A., et al.: Extraction of the minority carrier transport properties of solar cells using the Hovel model and genetic algorithms. *Measure. Sci. Technol.* **31**(2), 9 (2020). Article ID. 025601
30. Ji, G.L.: A rule-based model for bankruptcy prediction based on an improved genetic ant colony algorithm. *Math. Prob. Eng.* (2013). Article ID. 753251
31. Ji, G.: Genetic pattern search and its application to brain image classification. *Math. Prob. Eng.* (2013). Article ID. 580876
32. Ahmad, F., et al.: Intelligent medical disease diagnosis using improved hybrid genetic algorithm–multilayer perceptron network. *J. Med. Syst.* **37**(2), 9934 (2013)
33. Stappenbeck, L.E., et al.: Pretesting of the German Vocal Fatigue Index (VFI-D)-transcultural translation and cross validation. *Hno* **68**, 7 (2020)
34. Jiang, X., et al.: Classification of Alzheimer's Disease via eight-layer convolutional neural network with batch normalization and dropout techniques. *J. Med. Imag. Health Inform.* **10** (5), 1040–1048 (2020)
35. Kang, C., et al.: A heuristic neural network structure relying on fuzzy logic for images scoring. *IEEE Trans. Fuzzy Syst.* **1**, 1 (2020)
36. Wang, S.-H., et al.: Cerebral micro-bleeding identification based on a nine-layer convolutional neural network with stochastic pooling. *Concurr. Comput. Pract. Experience* **32**(1), e5130 (2020)
37. Mao, X., et al.: Knowledge-Aided 2-D autofocus for spotlight SAR filtered backprojection imagery. *IEEE Trans. Geosci. Remote Sens.* **57**(11), 9041–9058 (2019)