

Received February 10, 2017, accepted February 23, 2017, date of publication March 30, 2017, date of current version May 17, 2017.

Digital Object Identifier 10.1109/ACCESS.2017.2689058

Liver Fibrosis Classification Based on Transfer Learning and FCNet for Ultrasound Images

DAN MENG¹, LIBO ZHANG², GUITAO CAO¹, WENMING CAO³, GUIXU ZHANG⁴, AND BING HU⁵

¹MOE Research Center for Software/Hardware Co-Design Engineering, East China Normal University, Shanghai 200062, China

²Institute of Software, Chinese Academy of Sciences, Beijing 100190, China

³College of Information Engineering, Shenzhen University, Shenzhen 518060, China

⁴School of Computer Science and Software Engineering, East China Normal University, Shanghai 200062, China

⁵Department of Ultrasound, Shanghai Jiaotong University Affiliated Sixth People's Hospital, Shanghai 200233, China

Corresponding author: Guitao Cao (gtcao@sei.ecnu.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 61375015, and in part by the NSFC-Zhejiang Joint Fund for the Integration of Industrialization and Informatization under Grant U1609220.

ABSTRACT Diagnostic ultrasound offers great improvements in diagnostic accuracy and robustness. However, it is difficult to make subjective and uniform diagnoses, because the quality of ultrasound images can be easily influenced by machine settings, the characteristics of ultrasonic waves, the interactions between ultrasound and body tissues, and other uncontrollable factors. In this paper, we propose a novel liver fibrosis classification method based on transfer learning (TL) using VGGNet and a deep classifier called fully connected network (FCNet). In case of insufficient samples, deep features extracted using TL strategy can provide sufficient classification information. These deep features are then sent to FCNet for the classification of different liver fibrosis statuses. With this framework, tests show that our deep features combined with the FCNet can provide suitable information to enable the construction of the most accurate prediction model when compared with other methods.

INDEX TERMS Deep neural networks, fully connected layers, transfer learning, liver fibrosis.

I. INTRODUCTION

The incidence and mortality of liver disease are increasing yearly on the global scale, and the etiology of liver disease is complex. Consequently, the questions of how to perform prospective diagnoses of liver diseases and how to develop personalized treatment plans are important medical problems that have attracted considerable attention in recent years. Traditional diagnostic methods mainly rely on histopathological examination based on liver biopsy. However, liver biopsy is invasive and can easily cause other complications. Therefore, with the development of ultrasonic imaging technology, ultrasonic-imaging-based diagnostic techniques are becoming some of the most important methods for the examination, diagnosis and interventional treatment of various types of clinical diseases by virtue of their significant advantages such as their real-time dynamics, high sensitivity, good operability and non-invasive diagnosis.

Diagnoses based on ultrasonic imaging technology are subject to two main limitations: (1) Image quality. The quality of an image is often influenced by many subtle factors such as motion of the machinery and equipment and the experience of the image capturing staff. (2) The doctor's personal

experience. A doctor usually assesses an ultrasound image through visual inspection, but the characteristics that can be identified by the human eye are limited. Moreover, the same ultrasonic image may be interpreted differently by doctors with different clinical experience. To overcome these limitations, methods based on image processing techniques for helping doctors to extract relevant image characteristics are gradually emerging in the medical field.

Ogawa *et al.* [1] distinguished the status of the liver according to seven image features. Wu *et al.* [2] proposed a new classification method based on a multi-resolution fractal feature vector and the textural features of a fractal Brownian motion model. Mojilovic *et al.* [3] took advantage of the transformed image obtained through wavelet decomposition. Yeh *et al.* [4] extracted features by utilizing the grey-level co-occurrence matrix and wavelet decomposition and then used a classifier based on the support vector machine (SVM) technique for classifying the liver fibrosis status. The limitations of the traditional methods discussed above lie mainly in the following three areas: (1) The setting of the characteristics is often based on subjective human experience. (2) The number of extracted features is very limited.

(3) The proposed methods of feature extraction cannot be dynamically optimized according to changes in the dataset. With the development of deep learning technology, however, a new paradigm of computer-aided medical treatment is emerging. Miotto *et al.* [5] presented a new learning method based on unsupervised depth characteristics; this method includes an automatic decoder for noise reduction consisting of three layers. The method can produce a general characterization of a patient from electronic healthcare records to make clinical predictive modelling more convenient. Nguyen *et al.* [6] constructed Deeppr based on a deep convolutional neural network (DCNN) to improve the accuracy of clinical diagnosis. Nie *et al.* [7] presented a sparse deep learning framework for building a set of information characterizing a user's health to enable the inference of possible diseases.

Inspired by work on deep learning models and their variants, this paper proposes a two-stage framework for the classification of liver ultrasound images. The proposed framework consists of a deep feature extraction stage based on the transfer learning strategy and a classification stage using a fully connected neural network (FCNet). The proposed framework learns useful deep features from clinical data, and based on the obtained features, an artificial neural network (ANN) technique is applied to learn how to partition a liver's status as normal, early-stage fibrosis (S1-S3) or late-stage fibrosis (S4).

The main contributions of this paper are as follows:

- A new liver fibrosis classification framework is presented, which mainly benefits from two important components: deep features obtained through transfer learning and a stable classification strategy based on FCNet. The transfer learning stage explores the feature representations of liver ultrasound images, and the classification accuracy is increased using the FCNet.
- The deep features obtained through transfer learning and the VGGNet architecture can provide robust feature representations for predicting liver status based on ultrasound images.
- Our proposed method is evaluated using samples that have been diagnosed by clinicians. The experimental results confirm that the classifications of liver fibrosis samples produced by our proposed model agree well with clinicians' diagnoses.

The remainder of this paper is organized as follows. Section 2 introduces the motivation for the proposed method, and Section 3 describes the proposed method in detail. Experimental results are presented in Section 4. Finally, the conclusion and plans for future work are presented in Section 5.

II. MOTIVATION

In the following, we attempt to answer two questions: 1) What will a DCNN see when we present it with a liver image? and 2) How can we refine the current classification strategy to improve the classification performance? In this section, we first discuss extensive experiments that have been

conducted based on transfer learning using VGGNet [8]. Then, we analyse the features learned by VGGNet [8], and finally, we present the reason why we use the proposed FCNet for classification instead of constructing a deeper network, as performed in [8] and [9].

A. TRANSFER LEARNING

As described in [10], transfer learning refers to the ability to share and transfer knowledge between different tasks. Previous work has demonstrated that deep learning offers advantages for transfer learning tasks because the features learned by deep neural networks can capture most of the meaningful information that is useful for classification [11].

In many real-world classification tasks, it is difficult to satisfy the assumption that the training data and the data to be classified share the same distribution and the same feature space. For example, suppose that we have trained an AlexNet [12] for an object classification task, but we now wish to evaluate the quality of images [13], [14], or we simply want to know how to take better selfies [15]. In the above cases, transfer learning has the potential to improve performance and reduce the effort required for data labelling. The detailed transfer learning process for liver fibrosis classification from ultrasound images using VGGNet [8] is described later in Section III-A.

Recent studies have found that heat maps are useful for feature analysis [16], [17]. Inspired by such a feature analysis strategy, we use heat maps obtained from liver fibrosis images to visualize the differences between different stages of liver fibrosis and whether deep features provide sufficient information for liver fibrosis classification. Heat maps for liver images representing three liver statuses are shown in Fig. 1.

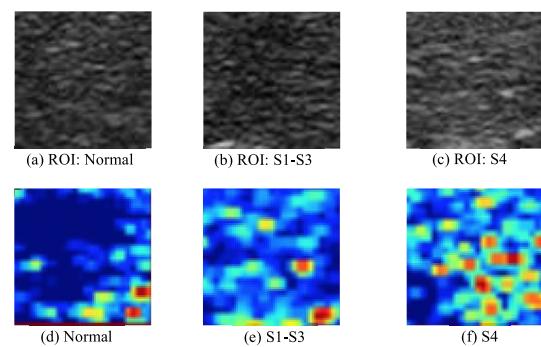


FIGURE 1. Samples showing original region-of-interest (ROI) ultrasound images and the corresponding heat maps for three different stages of liver fibrosis. (a)-(c) are the ROI ultrasound images, and (d)-(f) are the corresponding heat maps of the ultrasound images. These three images represent three liver statuses: normal (Normal), fibrosis stage 1-3 (S1-S3) and fibrosis stage 4 (S4), respectively.

B. FEATURE ANALYSIS

From Fig. 1, we can see that heat maps provide obvious clues for classifying the three represented liver statuses. Moreover, we observe that the colour of the activation regions in the heat maps is brighter when the texture information increases. We also plot histograms of these feature maps in Fig. 2.

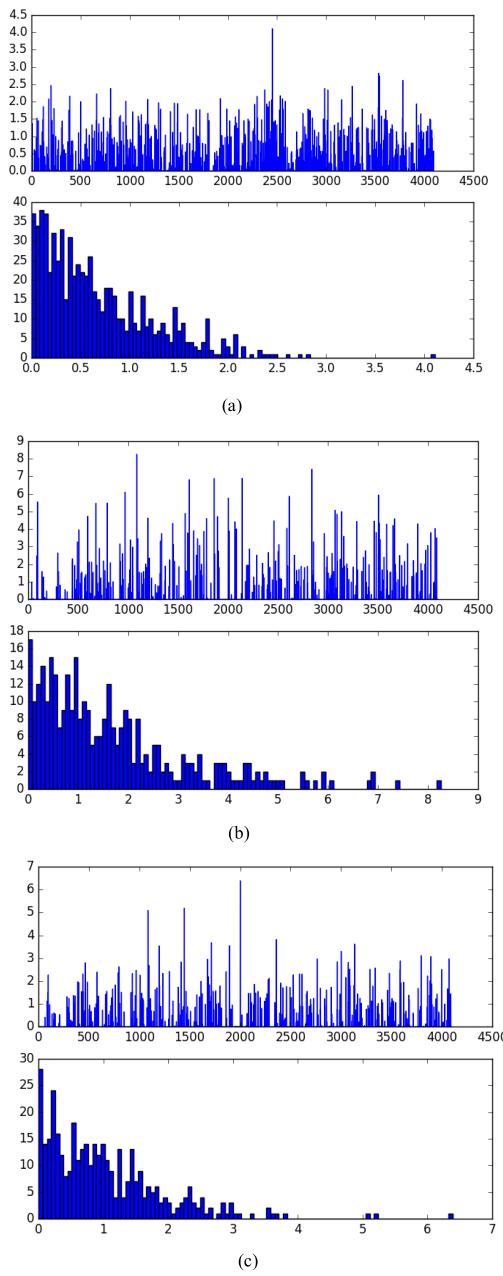


FIGURE 2. Histograms of feature maps in $fc7$ obtained from ultrasound images representing three different liver fibrosis stages: (a) normal (Normal), (b) early-stage fibrosis (S1-S3) and late-stage fibrosis (S4).

From a comparison, we find that fibrotic liver region-of-interest (ROI) images have much flatter texture distributions (the maximum histogram frequencies for normal liver, early-stage liver fibrosis, and late-stage liver fibrosis are 40, 18 and 30, respectively) and much wider intensity distributions than those of a normal liver (the maximum value for normal liver is only 4.5, whereas the maximum values for early-stage liver fibrosis and late-stage liver fibrosis are 9 and 7, respectively). These findings seem completely consistent with the observations reported in [18]. These phenomena indicate that the features learned by VGGNet [19] based on transfer

learning already provide sufficient classification information compared with the original ROI ultrasound images.

C. DEEPER NETWORK OR DEEPER CLASSIFIER?

Our dataset consists of a total of 279 ROI ultrasound images, including 79 healthy liver ROI images, 89 ROI images representing early-stage liver fibrosis, and 111 ROI images representing late-stage liver fibrosis. It is well known that a deeper network can achieve better performance. However, a deeper network also requires tens of thousands of images for training to avoid divergence, whereas we have only 279 ROI ultrasound images at hand. To improve the performance for this limited number of ROI ultrasound images, we design FCNet for liver status classification. The architecture of our proposed FCNet is detailed in Section III-B.

III. OUR APPROACH

Liver fibrosis classification based on ultrasound images can be regarded as a pattern recognition task. Such a task usually consists of two procedures: feature extraction and classification. In the following, we first introduce our feature extraction method, in which transfer learning is applied to achieve better performance. Then, we propose FCNet for deep-feature-based liver fibrosis classification.

A. DEEP FEATURE EXTRACTION METHOD BASED ON TRANSFER LEARNING

Instead of training a network from scratch, in our experiments, we use VGGNet pre-trained on the ILSVRC dataset [20]. VGGNet [8] is a DCNN that consists of five convolutional layers, three pooling layers and two 4096-dimensional fully connected layers followed by a 1000-way softmax layer. Inspired by VGGNet [8], and to make the deep features extracted by the DCNN more discriminative for the target task of liver fibrosis classification, we use the transfer learning technique to fine-tune the pre-trained VGGNet model on the ILSVRC dataset for the 3-way liver fibrosis classification task by using ROIs cropped from liver ultrasound images. The architecture used in this paper is shown in Fig. 3.

In particular, we replace the last 1000-way fully connected layer ($fc8$) with a new 3-way layer ($fc8_liver$) with randomly initialized weights W drawn from a normal distribution as follows: $W \sim N(\mu = 1, \sigma^2 = 0.01)$. We set the learning rate for transfer learning as suggested in [16] and [21]. We initialize the global rate to one tenth of the initial learning rate for the ILSVRC dataset [20] and decrease it by a factor of 10 throughout training; however, the learning rate in the new $fc8_liver$ layer is set 10 times higher than the global learning rate.

B. CLASSIFICATION USING FCNet

From Section III-A, we observe that a DCNN can tell the difference between normal liver images and abnormal liver images, and furthermore, it can distinguish between different stages of liver fibrosis. This suggests that the deep features

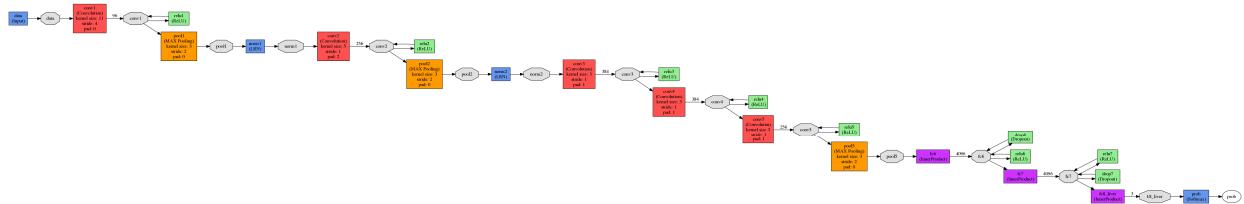


FIGURE 3. The architecture of our deep feature extraction method.

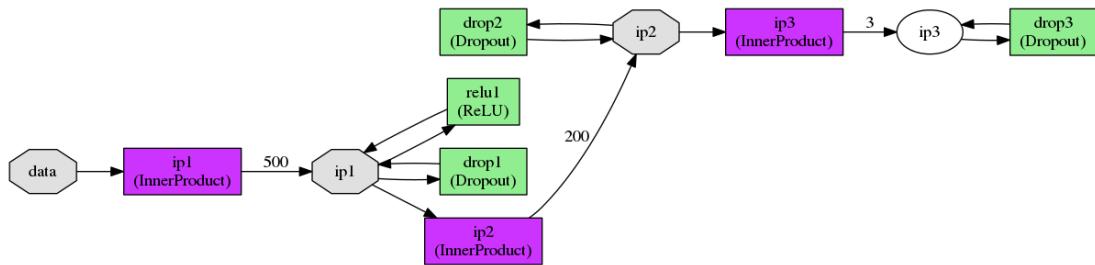


FIGURE 4. The architecture of our proposed fully connected neural network (FCNet).

extracted in this way can be effectively used for classification via a fully connected network, as these features contain rich information. Because the number of liver ultrasound images we have collected is small, establishing a deeper network and training a network from scratch is not feasible. However, we may attempt to feed the deep features obtained from the previous step into another neural network, which can be considered an alternative means of constructing a deeper network.

We propose a new classifier based on FCNet to improve the classification performance for liver images. The architecture of our proposed FCNet is shown in Fig. 4. Our FCNet takes the 4096-dimensional *fc7* features extracted by the previous deep feature extraction model as its input, and it consists of three fully connected layers (*ip1*, *ip2* and *ip3*). To avoid overfitting, we adopt the “dropout” strategy (following [22]). Specifically, for every fully connected layer, we add a corresponding dropout layer (*drop1*, *drop2* and *drop3*, respectively). We also include a Rectified Linear Units (ReLU) layer (*relu1*) after the first fully connected layer (*ip1*) to address the gradient vanishing problem [23]. We use formula (1) to compute the loss of our FCNet model:

$$E(W, b) = -\frac{1}{N} \sum_{n=1}^N [y_n \log \sigma_{W,b}(x_n) + (1 - y_n) \log(1 - \sigma_{W,b}(x_n))] \quad (1)$$

where $\sigma_{W,b}(x_n) = \frac{1}{1 + \exp(-W^T x_n)}$, N is the number of training samples, and $y_n \in \{0, 1, 2\}$ is the true label of the n th liver sample image, where $y_n = 0$ denotes that the status of the imaged liver is normal and $y_n = 1$ and $y_n = 2$ indicate liver images representing S1-S3 fibrosis and S4 fibrosis, respectively. In the back-propagation stage, we use formula (2) to calculate partial derivatives, which will be used in

the stochastic gradient decent (SGD) algorithm to find the optimal solution for formula (1).

$$\begin{aligned} \frac{\partial E(W, b)}{\partial x_n} &= \frac{\partial E(W, b)}{\partial \sigma_{W,b}(x_n)} \frac{\partial \sigma_{W,b}(x_n)}{\partial x_n} \\ &= -\frac{1}{N} \left(y_n \frac{1}{\sigma(x_n)} - \frac{1 - y_n}{1 - \sigma(x_n)} \right. \\ &\quad \times (\sigma_{W,b}(x_n) (1 - \sigma_{W,b}(x_n))) \Big) \\ &= \frac{1}{N} (\sigma_{W,b}(x_n) - y_n) \end{aligned} \quad (2)$$

Given a test sample x_j , the final classification is given by

$$[prob, C] = \max(W^T x_j + b) \quad (3)$$

where W and b are the parameters learned during the training stage and $prob$ denotes the probability that sample x_j belongs to class C .

IV. EXPERIMENTS

In this section, we evaluate and analyse the performance of our proposed method and compare it with state-of-the-art algorithms. Raw liver fibrosis ultrasound image samples were acquired from Shanghai Jiaotong University Number Six People’s Hospital. We collected only 279 cases; more cases will be obtained through practical application. The 279 collected cases include 79 normal ROI ultrasound liver images, 89 early-stage fibrosis ROI images and 111 late-stage fibrosis ROI images, as diagnosed by clinicians. To perform the liver fibrosis classification task, before fine-tuning, we cropped every ROI image from four directions in steps of 2 pixels with zero padding (see Fig. 5), and we flipped every ROI image horizontally and vertically. Thus, in addition to the original 279 ROI liver fibrosis images (image set A), we

TABLE 1. Performance comparison on liver fibrosis images.

	Trained on 70% of Set B			Trained on 70% of Set A		
	Test: 30% of Set B	Test: Set A	Test: 30% of Set B + Set A	Test: 30% of Set A	Test: Set B	Test: 30% of Set A + Set B
AlexNet [12]	84.65%	90.32%	86.66%	61.90%	82.21%	81.25%
CaffeNet [19]	89.37%	97.13%	92.12%	64.28%	75.83%	75.28%
VGGNet [8]	87.40%	96.41%	90.59%	66.67%	77.60%	77.08%
VGGNet-A + RF	85.04%	96.77%	89.20%	66.67%	78.61%	78.04%
VGGNet-B + RF	91.92%	97.13%	93.77%	61.90%	81.32%	80.41%
VGGNet-C + RF	91.93%	99.28%	94.54%	61.90%	82.27%	81.32%
VGGNet-D + RF	92.13%	99.64%	94.79%	64.29%	82.33%	81.48%
VGGNet-A + SVM	83.27%	93.55%	86.91%	65.48%	80.67%	79.95%
VGGNet-B + SVM	92.91%	100.00%	95.42%	61.90%	82.38%	81.41%
VGGNet-C + SVM	91.53%	97.13%	93.52%	65.47%	80.67%	79.95%
VGGNet-D + SVM	93.70%	99.64%	95.80%	64.29%	82.15%	81.31%
VGGNet-A + GBDT	81.88%	88.17%	84.12%	59.52%	79.37%	78.34%
VGGNet-B + GBDT	91.54%	98.57%	94.03%	64.29%	82.15%	81.31%
VGGNet-C + GBDT	82.28%	89.61%	84.88%	60.71%	79.14%	78.27%
VGGNet-D + GBDT	92.72%	99.28%	95.04%	63.10%	80.61%	79.79%
VGGNet-A + MLP	83.47%	90.32%	85.89%	65.47%	79.43%	78.77%
VGGNet-B + MLP	92.32%	99.64%	94.92%	61.90%	80.73%	79.84%
VGGNet-C + MLP	87.60%	94.62%	90.08%	65.64%	79.43%	78.77%
VGGNet-D + MLP	92.52%	99.64%	95.04%	64.29%	82.03%	81.19%
Our Method	93.90%	100.00%	96.06%	63.28%	83.03%	82.10%

All results in the table were achieved using the transfer learning strategy. VGGNet-A and VGGNet-C represent the fc6 and fc7 features, respectively, obtained by VGGNet without normalization. VGGNet-B and VGGNet-D represent the fc6 and fc7 features, respectively, obtained by VGGNet with normalization. VGGNet-i + CLF_i represents the features obtained by the fc6/fc7 layers of VGGNet and then classified by CLF_i, where CLF_i represents one of the flowing classifiers: RF, SVM, GBDT, and MLP.

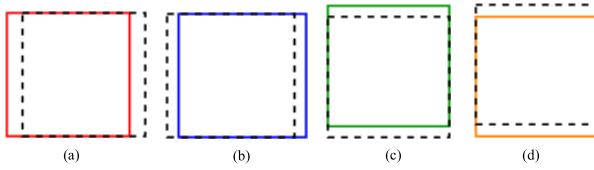


FIGURE 5. Examples of the cropping of one image from four directions in steps of 2 pixels with zero padding: (a) from the left, (b) from the right, (c) from the top and (d) from the bottom. The black dashed rectangle represents the original ROI liver image, and the rectangles in red, blue, green and orange represent the image as cropped from the left, right, top and bottom, respectively.

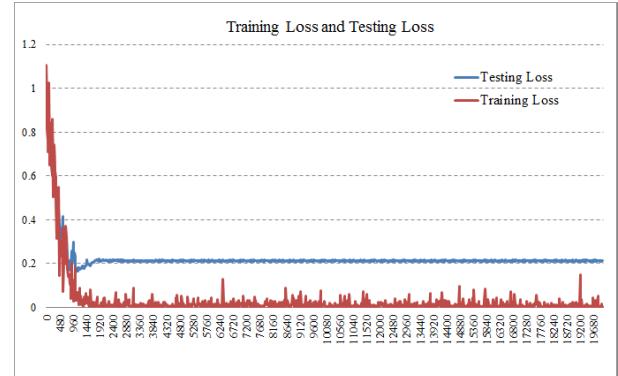


FIGURE 6. Training and testing losses in liver fibrosis classification based on VGGNet and transfer learning.

obtained 1674 further ROI ultrasound images (image set B). For the learning of deep features via transfer learning, we used image set B to fine-tune the VGGNet model as described in Section III-A.

We randomly chose 70% of the ROI images in image set B as the training set for transfer learning and used the remaining 30% of the images as the test set. Our feature extraction model is a snapshot of the 20000th iteration.

The loss during training fluctuated from 0.003 to 0.001 (see Fig. 6), and the testing loss was approximately 0.02 during the testing stage. Over-fitting occurred during the training stage, resulting in lower accuracy on the test set. Notably, the DCNN did its utmost to differentiate among different liver fibrosis statuses, as analysed in Section II-B.

After fine-tuning, we extracted deep features from the 1674 ROI liver images in image set B based on the fine-tuned model and fed these features into our proposed FCNet classifier. Again, we used the same 70% of the ROI images that were used for transfer learning as the training set to train the FCNet classifier, and the other 30% of the images were

used as the test set. Then, we tested the proposed liver fibrosis framework using 30% of the images in set B, the 279 images in image set A, and the test set from set B combined with the entirety of set A. The performances are shown in Table 1.

In Table 1, in addition to recent state-of-the-art DCNN architectures such as AlexNet [12], CaffeNet [19], and VGGNet [8], we also compare our proposed method with combinations of the deep features extracted by VGGNet [8] and four classical machine learning classifiers (Random Forest, SVM, Gradient Boosting Decision Tree and Multi-layer Perceptron). In Table 1, VGGNet-A and VGGNet-C represent the fc6 and fc7 features, respectively, obtained by VGGNet without normalization, and VGGNet-B and VGGNet-D represent the fc6 and fc7 features, respectively, obtained by VGGNet with normalization. From Table 1, we can draw the following conclusions:

1) VGGNet achieves the best performance when compared with AlexNet and CaffeNet, which indicates that a deeper network achieves better performance. As a result, it is clear that our proposed method should achieve the best performance because it can be regarded as an alternative means of cascading three fully connected layers after VGGNet. 2) The features generated by the fc7 layer are more discriminative than the features obtained from the fc6 layer, as features that are closer to the final output layer have a higher capability of abstraction. 3) Classifiers are sensitive to feature normalization. For example, VGGNet-B and VGGNet-D always perform better compared with VGGNet-A and VGGNet-C. 4) More training data can also contribute to improving the performance of DCNNs, as seen from the fact that the performance improves considerably when we expand the size of the training set from 70% of image set A to 70% of image set B.

V. CONCLUSION

In this paper, we proposed a new framework for liver fibrosis classification based on ultrasound images using transfer learning and FCNet. We learned deep features via transfer learning and VGGNet and trained a fully connected network (FCNet) classifier to predict normal, early-stage fibrosis and late-stage stage fibrosis liver statuses. With this novel framework, tests show that our deep features combined with the FCNet can provide suitable information to enable the construction of the most accurate prediction model when compared with other methods. In our future studies, we would like to develop a real-time computer-aided ultrasound image diagnosis system for liver fibrosis based on this approach.

REFERENCES

- [1] K. Ogawa, M. Fukushima, K. Kubota, and N. Hisa, "Computer-aided diagnostic system for diffuse liver diseases with ultrasonography by neural networks," *IEEE Trans. Nucl. Sci.*, vol. 45, no. 6, pp. 3069–3074, Dec. 1998.
- [2] C.-M. Wu, Y.-C. Chen, and K.-S. Hsieh, "Texture features for classification of ultrasonic liver images," *IEEE Trans. Med. Imag.*, vol. 11, no. 2, pp. 141–152, Jun. 1992.
- [3] A. Mojsilovic, S. Markovic, and M. Popovic, "Characterization of visually similar diffuse diseases from B-scan liver images with the nonseparable wavelet transform," *IEEE Trans. Med. Imag.*, vol. 17, no. 4, pp. 541–549, Oct. 1998.
- [4] W. C. Yeh, S. W. Huang, and P. C. Li, "Liver fibrosis grade classification with B-mode ultrasound," *Ultrasound Med. Biol.*, vol. 29, no. 9, pp. 1229–1235, 2003.
- [5] R. Miotto, L. Li, B. A. Kidd, and J. T. Dudley, "Deep patient: An unsupervised representation to predict the future of patients from the electronic health records," *Sci. Rep.*, vol. 6, p. 26094, May 2016.
- [6] P. Nguyen, T. Tran, N. Wickramasinghe, and S. Venkatesh, "DeepR: A convolutional net for medical records," *IEEE J. Biomed. Health Inform.*, vol. 21, no. 1, pp. 22–30, Jan. 2016.
- [7] L. Nie, M. Wang, L. Zhang, S. Yan, B. Zhang, and T. S. Chua, "Disease inference from health-related questions via sparse deep learning," *IEEE Trans. Knowl. Data Eng.*, vol. 27, no. 8, pp. 2107–2119, Aug. 2015.
- [8] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in *Proc. 5th Int. Conf. Learn. Represent.*, 2015, p. 1.
- [9] C. Szegedy et al., "Going deeper with convolutions," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2015, pp. 1–9.
- [10] Y. Bengio, A. Courville, and P. Vincent, "Representation learning: A review and new perspectives," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 35, no. 8, pp. 1798–1828, Aug. 2013.
- [11] S. J. Pan and Q. Yang, "A survey on transfer learning," *IEEE Trans. Knowl. Data Eng.*, vol. 22, no. 10, pp. 1345–1359, Oct. 2010.
- [12] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Proc. Adv. Neural Inf. Process. Syst. (NIPS)*, 2012, pp. 1097–1105.
- [13] W. Hou, X. Gao, D. Tao, and X. Li, "Blind image quality assessment via deep learning," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 26, no. 6, pp. 1275–1286, Jun. 2015.
- [14] K. Gu, G. Zhai, X. Yang, and W. Zhang, "Deep learning network for blind image quality assessment," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, May 2014, pp. 511–515.
- [15] A. Karpathy, *Liver Fibrosis Classification Based on Transfer Learning and FCNet for Ultrasound Images*, accessed on Oct. 25, 2015. [Online]. Available: <http://karpathy.github.io/2015/10/25/selfie/>
- [16] C. Huang, Z. He, G. Cao, and W. Cao, "Task-driven progressive part localization for fine-grained object recognition," *IEEE Trans. Multimedia*, vol. 18, no. 12, pp. 2372–2383, Dec. 2016.
- [17] G. Ghiasi and C. Fowlkes, "Laplacian pyramid reconstruction and refinement for semantic segmentation," in *Proc. 14th Eur. Conf. Comput. Vis.*, 2016, pp. 519–534.
- [18] G. Cao, P. Shi, and B. Hu, "Liver fibrosis identification based on ultrasound images captured under varied imaging protocols," *J. Zhejiang Univ. Sci.*, vol. 445, pp. 1107–1114, Jan. 2005.
- [19] Y. Jia et al., "CAFFE: Convolutional architecture for fast feature embedding," in *Proc. 22nd ACM Int. Conf. Multimedia*, 2014, p. 675.
- [20] O. Russakovsky et al., "ImageNet large scale visual recognition challenge," in *Proc. Int. J. Comput. Vis.*, 2015, p. 211.
- [21] K. He, X. Zhang, S. Ren, and J. Sun, "Spatial pyramid pooling in deep convolutional networks for visual recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 37, no. 9, pp. 1904–1916, Sep. 2015.
- [22] G. E. Hinton, N. Srivastava, A. Krizhevsky, I. Sutskever, and R. R. Salakhutdinov, "Improving neural networks by preventing co-adaptation of feature detectors," *Comput. Sci.*, vol. 3, pp. 212–223, Mar. 2012.
- [23] X. Glorot, A. Bordes, and Y. Bengio, "Deep sparse rectifier neural networks," *J. Mach. Learn. Res.*, vol. 15, pp. 315–323, Jun. 2010.



DAN MENG received the B.S. degree from the School of Computer Science and Software Engineering, East China Normal University, Shanghai, China, in 2012, where she is currently pursuing the Ph.D. degree. Her research interests include image processing, pattern recognition, and machine learning.



LIBO ZHANG received the bachelor's degree in microelectronics from Anhui University and the master's degree in electric engineering from the University of Electronic Science and Technology of China. He is currently pursuing the Ph.D. degree with the University of Chinese Academy of Sciences, Beijing, China. His research interests include image processing, pattern recognition, knowledge graph, and deep learning.



GUITAO CAO received the M.S. degree from Shandong University, Jinan, China, in 2001, and the Ph.D. degree from Shanghai Jiao Tong University, Shanghai, China, in 2006. She is currently an Associate Professor with the School of Computer Science and Software Engineering, East China Normal University, Shanghai, China. She has authored over 40 publications, including the IEEE TRANSACTIONS ON CYBERNETICS/IEEE TRANSACTIONS ON MULTIMEDIA/IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING. Her research interests include artificial intelligence, medical image analysis, and pattern recognition.



WENMING CAO received the M.S. degree from the System Science Institute, China Science Academy, Beijing, China, in 1991, and the Ph.D. degree from the School of Automation, Southeast University, Nanjing, China, in 2003.

From 2005 to 2007, he was a Post-Doctoral Researcher with the Institute of Semiconductors, Chinese Academy of Sciences, Beijing, China. He is currently a Professor with Shenzhen University, Shenzhen, China. He has authored or co-authored over 80 publications in top-tier conferences and journals. His research interests include pattern recognition, image processing, and visual tracking.



BING HU was born in 1959. He received the master's degree in biomedical engineering from the School of Medicine, Shanghai Jiao Tong University, in 1990, under the supervision of Prof. Y. Zhou.

He was a Professor, a Chief Physician, and a Doctoral Supervisor. He is currently the Director of the Department of Ultrasound in Medicine, Shanghai Jiao Tong University Affiliated Sixth People's Hospital and the Shanghai Institute of Ultrasound in Medicine, and also the Deputy Director of the Medical Imaging Research Institute, Shanghai Jiao Tong University. He has authored over 50 papers in SCI, obtained one national invention patent, Conformal Radiofrequency Ablation Electrode of Localized Prostate Cancer.



GUIXU ZHANG received the Ph.D. degree from the Institute of Modern Physics, Chinese Academy of Sciences, Lanzhou, China, in 1998. He is currently a Professor with the School of Computer Science and Software Engineering, East China Normal University, Shanghai, China. His research interests include hyperspectral remote sensing, image processing, and artificial intelligence.