[1.]Özkan İNİK, [2.]Esra BALCIOĞLU, [3.]Ayşe CEYHAN, [4.]Erkan ÜLKER

USING CONVOLUTION NEURAL NETWORK FOR CLASSIFICATION OF DIFFERENT TISSUE IMAGES IN HISTOLOGICAL SECTIONS

[1.]Gaziosmanpaşa University, Department of Computer Engineering, Tokat, TURKEY
[2-3.]Erciyes University School of Medicine, Department of Histology and Embryology, Kayseri, TURKEY
[4.]Selçuk University, Department of Computer Engineering, Konya, TURKEY

Abstract: Nowadays, medical images have been studied extensively using artificial intelligence methods. Especially deep learning models have been used frequently in diagnostic and identification systems in medical images. Many researchers and health experts work on the identification, counting and morphological characterization of tissue cells in histological sections. When these tasks are performed manually, time and workload are increased. For this reason, a fully automatic system is required to be made on the cells in the tissues. For a comprehensive operation of the system to be designed, it is first necessary to identify the tissues and then work on the cells forming the tissue. Due to this reason, in this study 5 different tissues were automatically classified. These tissues are Eye, Kidney, Liver, Ovary and Cerebellum respectively. A new Convolution Neural Network (CNN) is designed for classification. The input image size of the network is 220x220x3 and consists of 24 layers in total. A new data set has been created for this CNN training and testing. This data set is composed of 20500 images each class and totally 102500 image. 60% of these images were used for training and the remaining were used for testing. As a result of the study, it was seen that 5 different tissue were estimated with 96.47% accuracy with designed CNN.
Keywords: medical images, diagnostic and identification systems, artificial intelligence methods

1. INTRODUCTION

The Convolution Neural Network (CNN) was first used by Yann LeCun [1] to handwriting recognition. CNN have used wide area after ImageNet Large Scale Visual Recognition Challenge (ILSVRC)[2] at the 2012. In this competition, Alexnet[3] model, which is used with CNN base, won with 15.4% top-5 error rate. Image classification error rate is decreased from 26.2% to 15.4% with AlexNet model. This decline is a very sharp decline. This sharp drop in error rate in object classification has attracted the attention of all researchers.

After 2012, all participants used deep learning models in this competition as seen in Figure 1. Thus, the object classification error rate has dropped to 3% in this competition. This rate is lower than human error rate.

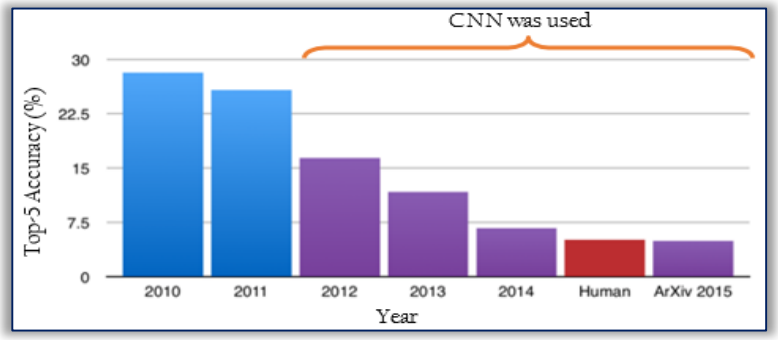

Figure 1. Top-5 error rate over the years in ImageNet competition

CNN architecture has been used in almost all areas since 2012. Analysis of medical images is at the forefront of these areas. In particular, CNN-based models have been used in cell classification [4-11], classification of lesions and brain diseases[12-19] and different medical applications[10, 20-24].

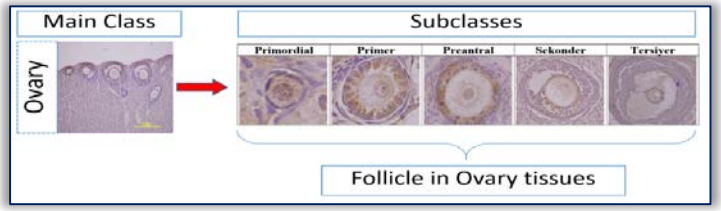

Figure 2. Five different follicles which forming ovarian tissue

Classifying, defining, counting, and calculating the cells or structure (belongs to many cells) in a tissue are frequently performed in medical faculties. These operations are always done manually. In order to perform these processes fully automatically, it is first necessary to classify the tissues and then to classify the cells forming the tissue. For example, there are 5 different follicles in the ovary as seen at the Figure 2. For the automatic classification of these follicles, the ovarian tissue must first be identified automatically from the other tissues. For this reason, in this study, firstly, we classified the tissues.

The content of this study is as follows; In the Chapter 2, information about the data set is given. In Chapter 3, structure of CNN model and information about the new CNN model is explained. Experimental studies and their results are presented in Chapter 4. Finally, the conclusion of the study is given in Chapter 5.

2. MATERIALS AND METHOD

– Data Set

A total of 5 different tissues were used in this study. These tissues were obtained from the medical faculty of Erciyes University. In Figure 3, a flow diagram of image acquisition from tissues is given. Sections were taken from tissues and images were obtained with a microscope from each section. A sample representation for the images obtained from tissues is given in Figure 3. 20500 images were obtained from each tissue section and totally 20500 images were obtained. 60% of the images were used for training and rest of images used for testing. In this study, data sets with different input image sizes were created when different CNN models were designed. These are 64x64x3, 128x128x3 and 220x220x3 respectively.

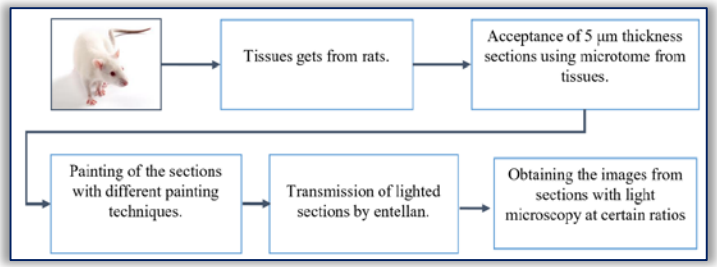

Figure 3. Flow diagram of obtaining histology images

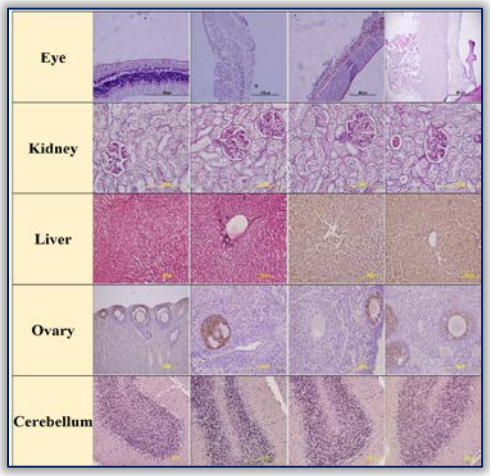

Figure 4. Images taken from histological sections of 5 different tissues

– Convolution Neural Network(CNN)

CNN is regarded as the basic architecture of Deep Learning. Generally, CNN consists of convolution, Relu, Pooling and a fully connected layer. Different CNN models can be designed with different numbers and different order from these layers. The convolution layer is the most important layer at the CNN models. Because of the learning process takes place through the filters in this layer. The number and size of filters to be used in each convolution layer are determined depending on the experience. The filters in the convolution layer are applied to the previous layer to form the activation or feature maps. For example, if 64 filters are defined in a convolution layer, each filter is applied to the image in the previous layer to form an output image and totally 64 images which known as Feature maps was created. The purpose here is that each filter will discover information about the object in the image.

After the convolution layer comes the pooling layer to reduce the size and prevent the overfitting of the network. Pooling can be done in different ways. However, due to its success mostly maxpooling is performed.

After pooling, the fully connected layer comes. Each neuron in the fully connected layer is connected to all previous neurons. The DroupOut[25] layer comes after the fully connected layer. The basic operation in this layer is to disable some neurons at random. Thus, the overfitting of the network is prevented. Finally, the softmax layer comes in and the classification is done on this layer [26].

In this study, a new CNN model consisting of a total of 24 layers was designed. The properties of the parameters used in each layer of the model are given in Figure 5.

Layer Number	Layer Name	Layer Properties		
1	Input Layer	Size: 220x220x3		
2	Convolution Layer	Filter Num.:64	Filter Size:3x3	Stride:1x1
3	ReLu Layer	-	-	-
4	Convolution Layer	Filter Num.:64	Filter Size:3x3	Stride:1x1
5	ReLu Layer	-	-	-
6	Pooling Layer	Max Pooling	Filter Size:2x2	Stride:2x2
7	Convolution Layer	Filter Num.:64	Filter Size:3x3	Stride:1x1
8	ReLu Layer	-	-	-
9	Convolution Layer	Filter Num:64	Filter Size:3x3	Stride:1x1
10	ReLu Layer	-	-	-
11	Pooling Layer	Max Pooling	Filter Size:2x2	Stride:2x2
12	Convolution Layer	Filter Num:128	Filter Size:3x3	Stride:1x1
13	ReLu Layer	-	-	-
14	Convolution Layer	Filter Num:128	Filter Size:3x3	Stride:1x1
15	ReLu Layer	-	-	-
16	Convolution Layer	Filter Num:128	Filter Size:3x3	Stride:1x1
17	ReLu Layer	-	-	-
18	Pooling Layer	Max Pooling	Filter Size:4x4	Stride:4x4
19	Full Connected Layer (1024)			
20	ReLu Layer			
21	DropOut Layer			
22	Full Connected Layer (5)			
23	softmaxLayer			
24	Classification Layer			

Figure 5. Parameter properties of the proposed CNN model

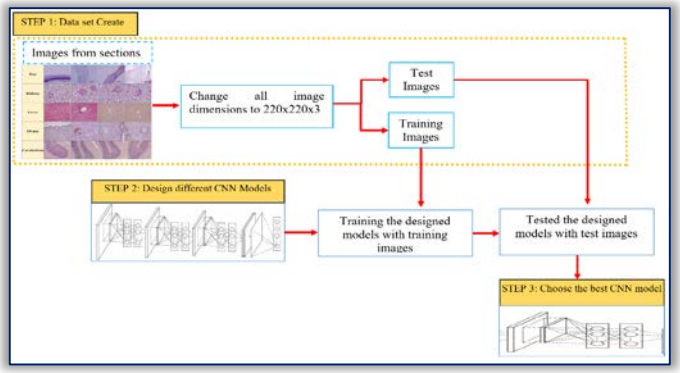

Figure 6. Flow diagram of the study

The studies were carried out three stages. As shown in Figure 6, firstly the images are reduced to 220x220x3 by taking images in RGB format. In this way, a new data set consisting

of 102500 images was created. These images were reserved for 60% training and 40% testing. Secondly, CNN models were designed in different number of layers and in their different sequence. More than one model was designed in this study. These designed models were trained with training data. After the test, the most ideal model was obtained.

3. EXPERIMENTAL STUDIES

In this work, Matlab R2017a 64bt (win64) is used as software platform. CNN models are built on GPU-based graphics cards. Intel Core i7 7700HQ 2.8GHz processor, 16GB Ram and GeForce GTX 1050 graphics card used for experimental studies used.

The decrease in the error value during training of the CNN model is given in Figure 7. Looking at Figure 7, we see that the model error closer to 0 in the training phase. The accuracy values of the model during training are shown in Figure 8. Referring to Figure 8 it is seen that the accuracy of the model approaches 100%.

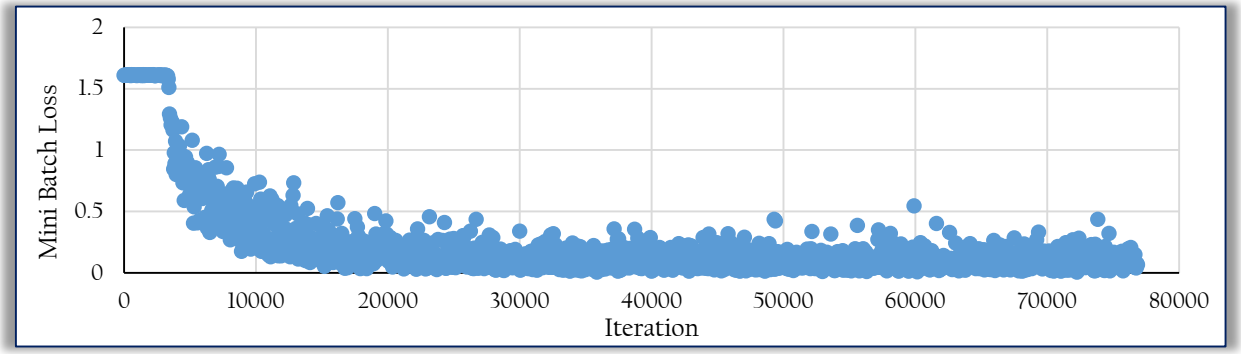

Figure 7. Error values of the designed model during the training phase

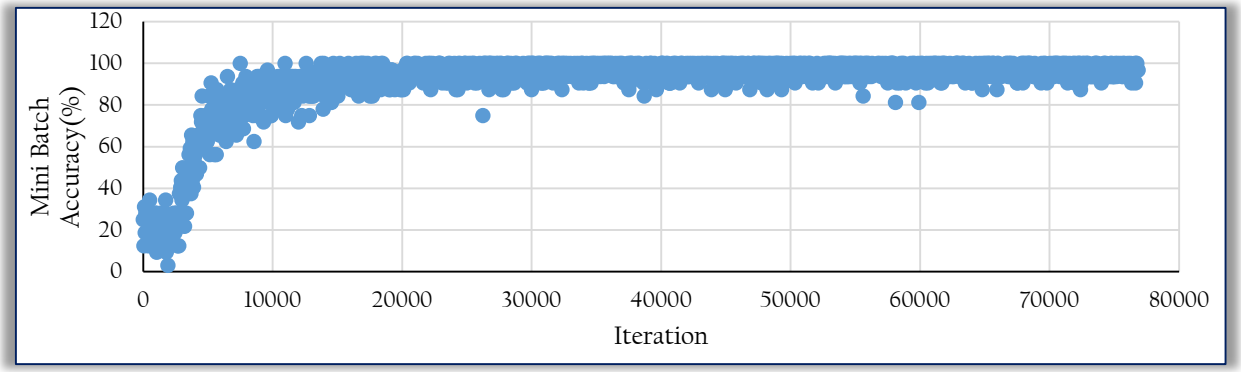

Figure 8. Accuracy values of the designed model at the training phase

The confusion matrix obtained in the testing after the training of the model is given in Figure 9. The accuracy value obtained in the testing is 96.47%. When we look at the confusion matrix, cerebellium tissue is mostly mixed with kidney, eye is mostly mixed with liver, liver is mostly mixed with kidney and ovary is mostly mixed with eye tissue.

		TARGET				
		CEREBELLIUM	EYE	KIDNEY	LIVER	OVARY
PREDICT	CEREBELLIUM	96.65	0.48	1.39	1.05	0.43
	EYE	0.34	97.53	1.12	0.06	0.96
	KIDNEY	1.13	0.90	94.60	3.03	0.35
	LIVER	0.58	0.12	2.97	96.25	0.08
	OVARY	0.06	2.42	0.16	0.01	97.35

Figure 9. Confusion matrix of the designed CNN model during the testing

4. CONCLUSION

In this study, a new CNN model was designed for the classification of 5 different tissues. A noval data set consisting of 102500 views was created for training and testing of the CNN model. As a result of the experimental studies, classification of 5 different tissues was done with 96.47% accuracy. Finally, this study proves that fully automated classification of cell in tissues can be done. So, we will work on the classification of cells in tissues in our future studies.

Note

This paper is based on the paper presented at INTERNATIONAL CONFERENCE ON APPLIED SCIENCES – ICAS 2018, organized by UNIVERSITY POLITEHNICA TIMISOARA, Faculty of Engineering Hunedoara (ROMANIA) and UNIVERSITY OF BANJA LUKA, Faculty of Mechanical Engineering (BOSNIA & HERZEGOVINA), in cooperation with the Academy of Romanian Scientists, Academy of Sciences Republic of Srpska, Academy of Technical Sciences of Romania – Timisoara Branch and General Association of Romanian Engineers – Hunedoara Branch, in Banja Luka, BOSNIA & HERZEGOVINA, 9 – 11 May 2018.

References

[1] Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," Proceedings of the IEEE, vol. 86, pp. 2278–2324, 1998.
[2] I. L. S. V. R. Competition, "Available online: http://www. image-net. org/challenges," LSVRC/, 2012.
[3] A. Krizhevsky, I. Sutskever, and G. Hinton, "ImageNet classification with deep convolutional neural networks," In NIPS'2012 . 23, 24, 27, 100, 200, 371, 456, 460, 2012.
[4] D. C. Cireşan, A. Giusti, L. M. Gambardella, and J. Schmidhuber, "Mitosis detection in breast cancer histology images with deep neural networks," in International Conference on Medical Image Computing and Computer-assisted Intervention, 2013, pp. 411-418.
[5] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in International Conference on Medical image computing and computer-assisted intervention, 2015, pp. 234-241.
[6] H. Chen, X. Qi, J.-Z. Cheng, and P.-A. Heng, "Deep Contextual Networks for Neuronal Structure Segmentation," in AAAI, 2016, pp. 1167-1173.
[7] A. Fakhry, H. Peng, and S. Ji, "Deep models for brain EM image segmentation: novel insights and improved performance," Bioinformatics, vol. 32, pp. 2352-2358, 2016.
[8] Y. Xie, F. Xing, X. Kong, H. Su, and L. Yang, "Beyond classification: structured regression for robust cell detection using convolutional neural network," in International Conference on Medical Image Computing and Computer-Assisted Intervention, 2015, pp. 358-365.
[9] Y. Xie, X. Kong, F. Xing, F. Liu, H. Su, and L. Yang, "Deep voting: A robust approach toward nucleus localization in microscopy images," in International Conference on Medical Image Computing and Computer-Assisted Intervention, 2015, pp. 374-382.
[10] H. Su, F. Xing, X. Kong, Y. Xie, S. Zhang, and L. Yang, "Robust cell detection and segmentation in histopathological images using sparse reconstruction and stacked denoising autoencoders," in International Conference on Medical Image Computing and Computer-Assisted Intervention, 2015, pp. 383-390.
[11] F. Liu and L. Yang, "A novel cell detection method using deep convolutional neural network and maximum-weight independent set," in Deep Learning and Convolutional Neural Networks for Medical Image Computing, ed: Springer, 2017, pp. 63-72.
[12] O. Maier, C. Schröder, N. D. Forkert, T. Martinetz, and H. Handels, "Classifiers for ischemic stroke lesion segmentation: a comparison study," PloS one, vol. 10, p. e0145118, 2015.
[13] T. Brosch, L. Y. Tang, Y. Yoo, D. K. Li, A. Traboulsee, and R. Tam, "Deep 3D convolutional encoder networks with shortcuts for multiscale feature integration applied to multiple sclerosis lesion segmentation," IEEE transactions on medical imaging, vol. 35, pp. 1229-1239, 2016.
[14] Q. Dou, H. Chen, L. Yu, L. Zhao, J. Qin, D. Wang, et al., "Automatic detection of cerebral microbleeds from MR images via 3D convolutional neural networks," IEEE transactions on medical imaging, vol. 35, pp. 1182-1195, 2016.
[15] M. Havaei, A. Davy, D. Warde-Farley, A. Biard, A. Courville, Y. Bengio, et al., "Brain tumor segmentation with deep neural networks," Medical image analysis, vol. 35, pp. 18-31, 2017.
[16] T. Brosch, R. Tam, and A. s. D. N. Initiative, "Manifold learning of brain MRIs by deep learning," in International Conference on Medical Image Computing and Computer-Assisted Intervention, 2013, pp. 633-640.
[17] H.-I. Suk, S.-W. Lee, D. Shen, and A. s. D. N. Initiative, "Hierarchical feature representation and multimodal fusion with deep learning for AD/MCI diagnosis," NeuroImage, vol. 101, pp. 569-582, 2014.
[18] B. C. Munsell, C.-Y. Wee, S. S. Keller, B. Weber, C. Elger, L. A. T. da Silva, et al., "Evaluation of machine learning algorithms for treatment outcome prediction in patients with epilepsy based on structural connectome data," Neuroimage, vol. 118, pp. 219-230, 2015.
[19] H.-I. Suk, C.-Y. Wee, S.-W. Lee, and D. Shen, "State-space model with deep learning for functional dynamics estimation in resting-state fMRI," NeuroImage, vol. 129, pp. 292-307, 2016.
[20] H.-C. Shin, M. R. Orton, D. J. Collins, S. J. Doran, and M. O. Leach, "Stacked autoencoders for unsupervised feature learning and multiple organ detection in a pilot study using 4D patient data," IEEE transactions on pattern analysis and machine intelligence, vol. 35, pp. 1930-1943, 2013.
[21] H.-I. Suk, S.-W. Lee, D. Shen, and A. s. D. N. Initiative, "Latent feature representation with stacked auto-encoder for AD/MCI diagnosis," Brain Structure and Function, vol. 220, pp. 841-859, 2015.
[22] G. Wu, M. Kim, Q. Wang, Y. Gao, S. Liao, and D. Shen, "Unsupervised deep feature learning for deformable registration of MR brain images," in International Conference on Medical Image Computing and Computer-Assisted Intervention, 2013, pp. 649-656.
[23] G. Wu, M. Kim, Q. Wang, B. C. Munsell, and D. Shen, "Scalable high-performance image registration framework by unsupervised deep feature representations learning," IEEE Transactions on Biomedical Engineering, vol. 63, pp. 1505-1516, 2016.
[24] J. Xu, L. Xiang, Q. Liu, H. Gilmore, J. Wu, J. Tang, et al., "Stacked sparse autoencoder (SSAE) for nuclei detection on breast cancer histopathology images," IEEE transactions on medical imaging, vol. 35, pp. 119-130, 2016.
[25] N. Srivastava, G. E. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: a simple way to prevent neural networks from overfitting," Journal of machine learning research, vol. 15, pp. 1929-1958, 2014.
[26] Ö. İNİK and E. ÜLKER, "Derin Öğrenme ve Görüntü Analizinde Kullanılan Derin Öğrenme Modelleri," 2017.

ISSN 1584 - 2665 (printed version); ISSN 2601 - 2332 (online); ISSN-L 1584 - 2665