LIVER TUMOR CLASSIFICATION WITH ADVANCED DEEP LEARNING TECHNIQUES

P.T Arshad, B.Firdaus Begam*

Abstract

The death rate of liver patients are high due to the diagnosis of the disease in the final stage. The deep learning technique helps to classify the type of disease at an early stage. This paper uses segmentation, feature extraction, and classification of liver cancer tissues to predict the type of cancer. Here, the augmentation-based auto-encoder framework is used for DL implementation with medical dataset integration. The anticipated deep learning model is used to create a deep network of restricted graph-based Boltzmann machine (RGBM) to define the activation of hidden unit nodes in RGBM as features and emphasize quantization by grouping these features in the method of unsupervised manner. Liver tissue classification used in medical imaging is designed by a novel 3D convolution neural network and used for discriminating normal and cancerous metastatic liver tissues from weighted MRI data.

Keywords: Encoder-Decoder Network, Boundary Segmentation, Image Segmentation, Medical Image Segmentation, Image classification, Continuous Network, Deep Convolutional Neural Network.

I. INTRODUCTION

In recent times, deep learning has offered a promising solution as a substitute instead of employing hand-crafted characteristics in computer vision tasks. As deep learners are E2E unsupervised feature extractors, they may either need or use domain-specific prior knowledge [1]. However, for human beings to achieve specified tasks, an insight can be achieved only through focused training in a specified domain, typically [2]. Henceforth, integrating domain-specific knowledge in some extend into learning techniques may validate these essential tasks.

Histopathological tissues can be examined for diagnosing and grading liver cancer. The pathologist with vast knowledge is needed for this process training to inspect visually a training sample [3]. In this analysis, the pathologist will not analyse the randomly chosen sub-regions however salient tissues pointed around the significant parts of the tissue. They initially determine the features of those salient sub-regions[4] and then appropriately classify them to determine whether the sample comprises aberrant (cancerous) or normal tissue formation [5]. This classification and decision-making process is based on expert knowledge and human insights [6]. Moreover, most of these sub-regions are inadequate in peculiar or clear explanations that can be openly used in supervised classifiers, and in this learning system, the annotation task of these sub-regions needs massive effort and high cost. Scattering coefficients (SC) will give consistent representations and plot the texture of fatty liver picture to an acumen copious, giving better features for classifications [7].

II. METHODOLOGY

This section explains the flow of the proposed model starting from segmentation, feature extraction, and classification of liver cancer tissues [4].

Segmentation

Here, a novel polyp segmentation approach based on multiple deep auto-encoder networks is used [8]. This model holds multiple-level textual information of dataset

Department of Computer Science,
Karpagam Academy of Higher Education, Coimbatore, Tamil Nadu, India
*Corresponding Author

images by segmenting separated features at diverse image scales and field views and acquires rich information regarding the features from lost pixels during the training phase. However, this network is capable of attaining object boundaries using multi-scale effective encoders [9]. A novel strategy for enhancing the segmentation process based on boundary augmentation with an auto-encoder is proposed to improve dice loss function. This objective of this scheme is to make the deep learning network to be available for poorly defined liver object boundaries that is caused due to non-specular transition zone amongst foreground and background regions.

Feature extraction

After performing segmentation, a feature extraction model has to be proposed to recognize salient sub-regions of liver tissues from the image segmented based on domain-specific prior knowledge and enumerate the picture by employing the features of these sub-regions considering the features of the entire image location [10]. Subsequently, a deep learning-based approach enumerates salient sub-regions by extracting features directly from image data and utilizing those quantization distributions for image classification and representation by a pathologist. Finally, the anticipated deep learning model builds networks of deeply restricted graph-based Boltzmann machine (RGBM) to point out activation values of hidden unit nodes in RGBM as features and emphasize quantization by grouping these features in an unsupervised manner. This graph-based modelling will be more effective in the histopathological domain of image analysis. The features extracted will be provided for further classification processes [11].

Classification

In the last phase, a novel 3D Convolutional neural network model is used for liver tissue classifications in medicals imaging and used for separating normal and cancerous metastatic liver tissues from weighted MRI data [12]. The anticipated model comprises 3D convolutional layers with kernel size and activation function (ReLU), followed by fully connected layers and soft max layers for binary classification [13]. The dataset comprises of roughly 130 scans which is used for validating and training of network [14]. Based on the literature, this investigation lays the initial deep learning solution for the clinical problem and liver tumour classification directly over tomographic data without performing any pre-processing steps like ROI detection, annotation, and tissue region cropping [15].

III. EXPECTED OUTCOME AND RELEVANCE OF STUDY

The following are the performance metrics to be extracted when diagnosing Liver cancer while performing image segmentation, feature extraction, and classification.

Accuracy
Specificity
Sensitivity
Dice
Precision
F1 score

The proposed model is compared with existing approaches like Salient stacked autoencoder, a randomly stacked autoencoder, Random convolution Autoencoder, Local object pattern [16].

IV.CONCLUSION AND CHALLENGES

The optimal feature selection and optimized classification models are used to reduce the error, complexity in computation, and classification accuracy in liver tumour classification. By optimizing the weight or number of hidden neurons of the restricted graph-based Boltzmann machine (RGBM), classification performance is improved. A novel 3D Convolutional neural network model is used for liver tissue classification in medicals imaging and used for separating normal and cancerous metastatic liver tissues from weighted MRI data. Deep autoencoders yield better compression compared to other techniques.

REFERENCES

[1] R. Bharath, and P. Rajalakshmi, "Deep scattering convolution network-based features for ultrasonic fatty liver tissue characterization," Conf Proc IEEE Eng Med Biol Soc, vol. 2017, pp. 1982-1985, 07, 2017.

[2] P. Moeskops, M. A. Viergever, A. M. Mendrik, L. S. de Vries, M. J. Benders, and I. Isgum, "Automatic Segmentation of MR Brain Images With a Convolutional Neural Network," IEEE Trans Med Imaging, vol. 35, no. 5, pp. 1252-1261, 05, 2016.

[3] T. Joyce, A. Chart sias, and S. A. Tsaftaris, "Deep Multi-Class Segmentation Without Ground-Truth Labels," 1st Conference on Medical Imaging with Deep Learning, Amsterdam, The Netherlands, 2018.

[4] J. Cai, L. Lu, Z. Zhang, F. Xing, L. Yang, and Q. Yin, "Pancreas Segmentation in MRI using Graph-Based Decision Fusion on Convolutional Neural Networks," Med Image Compute Assist Interv, vol. 9901, pp. 442-450, Oct, 2016.

[5] Q. Dou, L. Yu, H. Chen, Y. Jin, X. Yang, J. Qin, and P. A. Heng, "3D deeply supervised network for automated segmentation of volumetric medical images," Med Image Anal, vol. 41, pp. 40-54, Oct, 2017.

[6] A. Ben-Cohen, E. Klang, I. Diamant, N. Rozendorn, S. P. Raskin, E. Konen, M. M. Amitai, and H. Greenspan, "CT Image-based Decision Support System for Categorization of Liver Metastases Into Primary Cancer Sites: Initial Results," Acad Radiol, vol. 24, no. 12, pp. 1501-1509, Dec, 2017.

[7] K. Yasaka, H. Akai, O. Abe, and S. Kiryu, "Deep Learning with Convolutional Neural Network for Differentiation of Liver Masses at Dynamic Contrast-enhanced CT: A Preliminary Study," Radiology, vol. 286, no. 3, pp. 887-896, Mar, 2018.

[8] Q. Dou, H. Chen, Y. Jin, L. Yu, J. Qin, and P.-A. Heng, "3D Deeply Supervised Network for Automatic Liver Segmentation from CT Volumes," International Conference on Medical Image Computing and Computer-Assisted Intervention, pp. 149-157, 2016.

[9] W. Zhu, C. Liu, W. Fan, and X. Xie, "DeepLung: Deep 3D Dual-Path Nets for Automated Pulmonary Nodule Detection and Classification," IEEE Winter Conference on Applications of Computer Vision (WACV), pp. 673-681, 2018.

[10] G. Kang, K. Liu, B. Hou, and N. Zhang, "3D multi-view convolutional neural networks for lung nodule classification," PLoS One, vol. 12, no. 11, pp. e0188290, 2017.

[11] H. Donato, M. França, I. Candelária, and F. Caseiro-Alves, "Liver MRI: From basic protocol to advanced techniques," Eur J Radiol, vol. 93, pp. 30-39, Aug, 2017.

[12] K. Drevelegas, K. Nikiforaki, G. Manikis, K. Marias, M. Constantinides, I. Stoikou, L. Papalavrentios, P. Bangers and A. Drevelegas, "Classification of focal liver lesions based on histogram analysis of 3D pixel-based ADC parametric maps," ECR 2017–27th European Congress of Radiology, Vienna, Austria, March 1-5, 2017.

[13] G.C. Manikis, K. Nikiforaki, N. Papanikolaou, and K. Marias, "Diffusion Modelling Tool (DMT) for the analysis of Diffusion-Weighted Imaging (DWI) Magnetic Resonance Imaging (MRI) data," in

Proceedings of the 33rd Computer Graphics International, Heraklion, Greece, 2016.

[14] H. Rezaeilouyeh, A. Mollahosseini, and M. H. Mahoor, "Microscopic medical image classification framework via deep learning and shearlet transform," J. Med. Imaging, vol. 3, no. 4, pp. 044501, Oct. 2016.

[15] E. Ozdemir and C. Gunduz-Demir, "A hybrid classification model for digital pathology using structural and statistical pattern recognition," IEEE Trans. Med. Imaging, vol. 32, no. 2, pp. 474-483, Feb. 2013.

[16]Atrayee Dutta and Aditya Dubey, "Detection of Liver Cancer using Image Processing Techniques", Conf Proc IEEE Eng Med Biol Soc, vol. 2019, pp. 4-6 , April 2019.