

Lung Nodule Detection, Classification and Segmentation via Deep Learning

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Thesis submitted in fulfilment of the requirements for
the degree of

Doctor of Philosophy

under the supervision of Dr.Wenjing Jia

University of Technology Sydney
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Jun 2021

CERTIFICATE OF ORIGINAL AUTHORSHIP

I, Mohammad Hesam Hesamian declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Electrical and Data Engineering/Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

This research is supported by the Australian Government Research Training Program.

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Date: 25/06/2021

ABSTRACT

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Accurately detecting and segmenting lung nodules from CT images play a critical role in the earlier diagnosis of lung cancer, staging and evaluating patients' response to cancer therapy. Thus, this research area has attracted much interest from the research community. Moreover, deep learning based image segmentation has by now been firmly established as a robust tool in image segmentation. It has been widely used to separate homogeneous areas as the first and critical component of diagnosis and treatment pipeline.

In the first part of my research, an advanced solution is proposed to segment lung nodules from CT images by employing a deep residual network structure with Atrous convolution. The Atrous convolution increases the field of view of the filters and helps to improve classification accuracy.

Due to the irregular shapes of nodules, and the low-intensity contrast between the nodules and other lung areas, precisely segmenting nodules from lung CT images is a very challenging task. The second part of this research proposes a highly effective and robust solution to this problem by innovatively utilizing the changes of nodule shapes over continuous slices (inter-slice changes) and develops a deep learning based end-to-end system. Different from the existing 2.5D or 3D methods that attempt to explore the inter-slice features, we propose to create a novel synthetic image to depict the unique changing pattern of nodules between slices in distinctive colour patterns. By taking advantage of inter-slice information and forming the proposed synthetic image, the task of lung nodule segmentation can be done accurately.

To further improve the detection and segmentation accuracy, in the third part of this research, a two-stage segmentation method is developed which is capable of improving the accuracy of detection and segmentation of lung nodules from 2D CT images. The first stage of our approach proposes multiple regions, potentially containing the tumour, and the second stage performs the pixel-level segmentation from the resultant regions.

Dissertation directed by Dr Wenjing Jia
School of Electrical and Data Engineering

Dedication

This disertation is dedicated to my wonderful parents

Miham Nikfetrat

and

Naser Hesamian

who have given me endless love, encouragement and invaluable supports

throughout my life.

And my younger brother

who is my loveliest friend in life.

Acknowledgements

All praise and gratitude will be to Allah the Almighty for his mercy and support during our life and moments of truth.

First and foremost, I would acknowledge my dear supervisor Dr. Wenjing Jia for her continuous and endless supervisions and encouragements.

I would like to extend my thanks to Professor Sean He for his practical guides.

My deep gratitude to my co-supervisor, Professor Paul Kennedy, for his pure assistance and brotherly help not only in study but also in many other aspects that will never be forgotten.

I would also like to express my gratitude to Sharifah Farhana, who has given me moral support throughout the challenging times and shared even small happiness with me.

Mohammad Hesam Hesamian
Sydney, Australia, 2021.

List of Publications

Journal Papers

- J-1. Hesamian MH, Jia W, He X, Kennedy P. Deep Learning Techniques for Medical Image Segmentation: Achievements and Challenges. *Journal of digital imaging*. 2019 May 29:1-5.
- J-2. Hesamian MH, Jia W, He X, Qinqing Wang, Kennedy P. Synthetic CT Images for Semi-Sequential Detection and Segmentation of Lung Nodules. *Applied Intelligence*. 2020 August.

Conference Papers

- C-1. Hesamian MH, Jia W, He X, Kennedy PJ. Atrous Convolution for Binary Semantic Segmentation of Lung Nodule. In *ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) 2019* May 12 (pp. 1015-1019). IEEE.
- C-2. Hesamian MH, Jia W, He X, Kennedy PJ. Region Proposal Network for Lung Nodule Detection and Segmentation. In *ECAI 2020. European Conference on Artificial Intelligence*. September 2020.

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