

Evaluation of VGG & ResNet Very Deep Convolutional Neural Networks for Detecting Lung Cancer in CT Scans

W.P.H.D. Perera

168253V

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Department of Computer Science and Engineering

University of Moratuwa

Sri Lanka

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DECLARATION

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ABSTRACT

Lung cancer is the second most common destructive cancer in the world. It is important to detect Lung cancer at its earliest possible time because this dreadful illness spreads in a rapid pace weakening and killing the entire body of a human. The lung cancer identification process is not easy as its symptoms are visible to outside mostly at its final stage. Lung cancer nodules are detected by radiologists through CT (Computed tomography) scans, but there is a high probability to fail to spot where the actual lung cancer nodule is because, the lung lesions are low in contrast. Therefore, there should be a Computer Aided Diagnosis (CAD) system to assist radiologists in identifying lung nodules efficiently, accurately so the results given by the CAD systems can be taken as a second opinion to detect lung nodules for radiologists. Accurate CAD systems can improve the quality and productivity of radiologists' image interpretation. There are many research subjects ongoing in medical imaging and diagnostic radiology. But it is needed to continuously improve the accuracy and the consistency of radiological diagnoses because still there are high false positive rates associated with CAD system results.

Current CAD systems have been developed using two main different approaches. First is the conventional old framework which detects lung cancer nodules using manual feature extraction and conventional image preprocessing approach. New approach is the Deep Neural Network architecture which automatically and directly uncovers features from the training data. In this approach the three steps, feature extraction, selection and supervised classification have been realized within the optimization of the same deep architecture.

This research evaluates two existing very deep learning architectures, Resnet-50 and VGG19 for learning high-level image representation to achieve high classification accuracy with low variance in medical image binary classification tasks. The classification accuracy was performed with two different datasets, NDSB and LUNA16+LIDC. For NDSB dataset the Restnet-50 model outperformed VGG19 model by giving the accuracy, sensitivity and specificity as 68%, 73%, 65% respectively. And for LUNA16+LIDC dataset 80.3%, 79.8%, 80.6% results were obtained for accuracy sensitivity and specificity out performing again the VGG19 network architecture.

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