Malignant Lung Nodule Detection using Deep Learning

Amrit Sreekumar, Karthika Rajan Nair, Sneha Sudheer, Ganesh Nayar H and Jyothisha J Nair

***Abstract*—Lung Carcinoma, commonly known as Lung Cancer is an infectious lung tumour caused by uncontrollable tissue growth in the lungs. Presented here is an approach to detect malignant pulmonary nodules from CT scans using Deep Learning. A preprocessing pipeline was used to mask out the lung regions from the scans. The features were then extracted using a 3D CNN model based on the C3D network architecture. The LIDC-IDRI is the primary dataset used along with a few resources from the LUNA16 grand challenge for the reduction of false-positives. The end product is a model that predicts the coordinates of malignant pulmonary nodules and demarcates the corresponding areas from the CT scans. The final model achieved a sensitivity of 86 percent for detecting malignant Lung Nodules and predicting its malignancy scores.**

***Index Terms*—Lung Nodule Detection, Deep Learning, CT scans, Malignancy prediction and C3D network.**

I. Introduction

LUNG CANCER is most dominant reason for cancer-related deaths across the globe. The uncontrollable division of undesirable cells in the lung region can be classified as Lung Cancer. As their growth progresses, the abnormal cells form tumours and interfere with the normal functioning of the lungs [1]. Since there are no apparent signs or symptoms of early lung cancer, the clinical diagnosis of lung cancers are often late, making treatment expensive and ineffective [2]. Early diagnosis of cancer is critical for providing victims with the best treatment and the possibility of a revival [3]. Detection of Lung cancer in its early stages using CT scans would help save many lives, but analyzing the scans of the majority is an immeasurable burden for radiologists [4]. We have used a Deep Convolutional Neural Network (DCNN) and numerous preprocessing techniques to build up the exactness of the automated prediction of Lung nodules and its Malignancy using CT Scans. The Deep Convolutional Neural Networks, with superior object detection performance in natural images, is considered as the state of the art methodology in medical imaging and object detection applications as well [5]. Fig. 1 shows an outline of our proposed architecture with which the system works. We describe the proposed course of action, estimation, and final output using the LIDC-IDRI dataset and resources obtained from the LUNA16 challenge that supplement the dataset.

The paper is organized as follows. The system architecture and related works were explained in section II and section III respectively. The data sets resources, preprocessing, the extraction and detection are described in section IV and section V and section VI respectively. Section VII discussed about the results. At last paper concludes with the conclusion in section VIII.

Amrit Sreekumar, Computer Science & Engineering, Amrita Vishwa Vidyapeetham, Amritapuri, India; e-mail: amrit.sreekumar@gmail.com
Karthika Rajan Nair, Computer Science & Engineering, Amrita Vishwa Vidyapeetham, Ampritapuri, India; e-mail: karthikanair311@gmail.com
Sneha Sudheer, Computer Science & Engineering, Amrita Vishwa Vidyapeetham, Amritapuri, India; e-mail: snehasudheer660@gmail.com
Ganesh Nayar H, Computer Science & Engineering, Amrita Vishwa Vidyapeetham, Amritapuri, India; e-mail: ganeshharindranath.letha@gmail.com
Jyothisha J Nair, Computer Science & Engineering, Amrita Vishwa Vidyapeetham, Amritapuri, India; e-mail: jyothishaj@am.amrita.edu

II. Proposed System Architecture

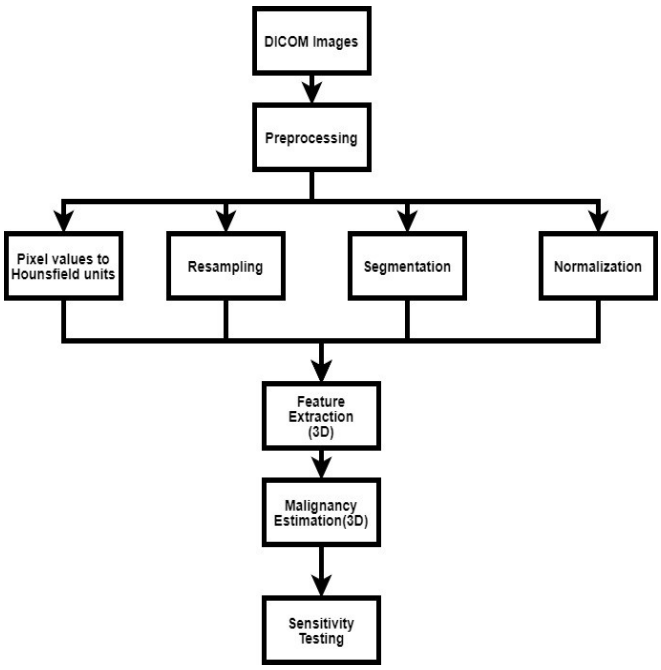

Fig. 1. System Architecture

978-1-7281-4988-2/20/$31.00 ©2020 IEEE

III. Related Work

Lung cancer is listed as one of the most outrageous disorders in developing nations. Lung cancer detection has earlier been overworked using image processing approaches. Neural Networks and Deep Learning techniques have recently been used in the medical imaging domain. Techniques such as convolutional neural networks (CNN), Deep Belief Networks (DBNs), and stat denoising autoencoder (SDAE) were used on the LIDC-IDRI dataset by Sun et al. Accuracies obtained for the same were 79%, 81%, and 79%, respectively [6].

The study conducted by the American Cancer Society shows that if lung cancer is found at an earlier stage when it is small and localized, it's more likely to be successfully treated. The National Lung Screening Trial (NLST), a trial held on 5000 stochastic subjects with a likelihood of detection of lung cancer, proved that when collated to the chest radiography technique, a computed tomography (CT) method of lung cancer screening reduces the yearly lung cancer mortality rate by a margin of 20% [7]. Manual analysis and diagnosis systems can significantly be improved with the implementation of image processing techniques. The neural network does a vital role in the recognition of cancer cells among the normal tissues, which in turn provides a useful tool for building assistive AI-based cancer detection technologies [8]. The dangerous nodules can be detected at an earlier stage by the radiologists using computed tomography (CT) and other scanning techniques [9].

The method proposed by Nasrullah Nasrullah et al. follows the objective of false-positive reduction at the initial stages. Initially, the lung CT image was put through 3D R-CNN with CMixNet and a U-Net-like encoder-decoder for the detection of nodules. Several factors such as patient family history, age, smoking history, clinical biomarkers, size, and location of the detected nodule were used for further evaluation of the results obtained from Deep Learning-based nodule classification, thereby significantly reducing the false positives [10].

The LUNA16 Challenge [11] aims to identify the possible nodule locations and allocate the likelihood of a nodule to be located at a specified point or location. The researcher Zatloukal et al. with the use of chemotherapy techniques studied the confinement of non-small and significant lung cancer cells. Later, Zhou et al. [12] presented a technique for cancer cell identification with the help of neural network ensembles. The Data Science Bowl 2017 [13] hosted by Kaggle aims to improve lung cancer detection by providing a platform for its participants to find algorithms that can be used for precise determination of lung cancer. The method developed by Chethan Dev et al. uses an SVM that takes in 33 features from the segmented lungs and classifies it as cancerous or non-cancerous. It has given better results than existing systems [14]. Sathyan H et al. classifies lung tumours into benign and malignant using AlexNet and transfer learning methodology. This method gives a 98% accuracy with a minimal false-positive rate [15].

IV. Dataset And Resources

The Lung Image Database Consortium image stack (LIDC-IDRI) comprises of diagnostic and lung cancer screening thoracic computed tomography (CT) scans with marked-up annotated lesions. This dataset is used for training the neural network and assessing computer-assisted diagnostic (CAD) techniques used for lung cancer detection and diagnosis. It contains 1018 CT scans from high-risk patients in the DICOM format. Each scan comprises a set of DICOM images that corresponds to the various axial slices of the chest cavity.

Metadata from the LIDC-IDRI dataset include XML files for each patient that has annotations of nodules and non-nodules done by 4 different thoracic radiologists [16]. The malignancy scores from 1 to 5 for each nodule present in the pulmonary region of subjects also adds to the metadata. An extended set of candidate locations in the form of a CSV file, sourced from the LUNA16 challenge [11], was also used for the reduction of false-positives during training.

V. Preprocessing

Given the heterogeneous nature of the DICOM files, some preprocessing was required before those images were fed into the neural network. Each slice of the scan is loaded into a python list. Since the difference in the pixel spacing of each scan can disturb the performance of the CNN, an isomorphic resampling was performed. The full dataset was resampled into a certain isotropic resolution of 1mm x 1mm x 1mm pixels. Post resampling, the pixels were converted into its corresponding Hounsfield units (a measure of radiodensity). This step was necessary to segment out the largest air pocket (ROI) from the lung region. The HU value was -1000 for the same [17]. Fig. 2 shows an axial cross-section of a lung after initial preprocessing techniques were applied. Fig. 3 plots the frequency vs. Hounsfield units graph for the same slice.

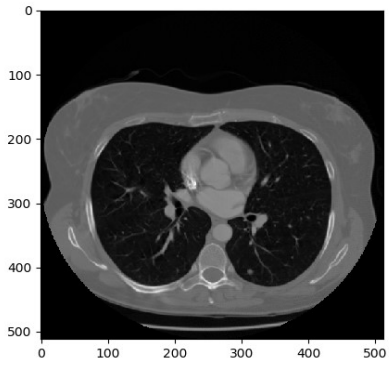

Fig. 2. Axial slice of the lung

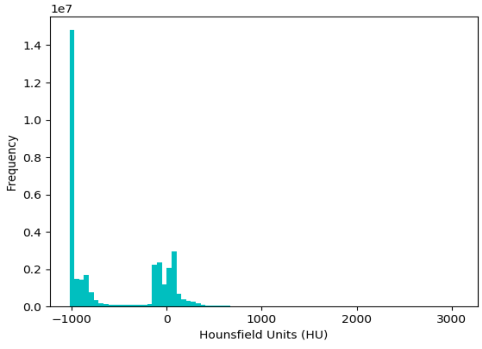

Fig. 3. Frequency-HU graph

Segmenting the lungs from the remaining CT scan reduces the problem space and hence feature extraction becomes more effective. Using connected component analysis to segment out the largest air pocket [17] was an effective way to single out the lung region. A dilation morphological operation was used as well to expand the mask in all directions so that the nodules stuck to walls of the lung were also included. Fig. 4 plots the CT scan in 3D. Fig. 5 visualizes the segmented pulmonary region.

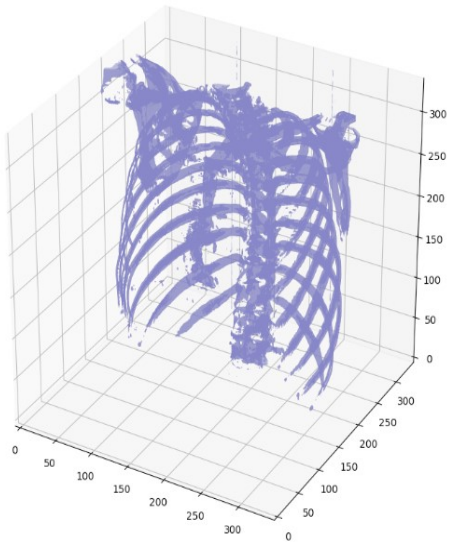

Fig. 4. 3D Plotted CT scan

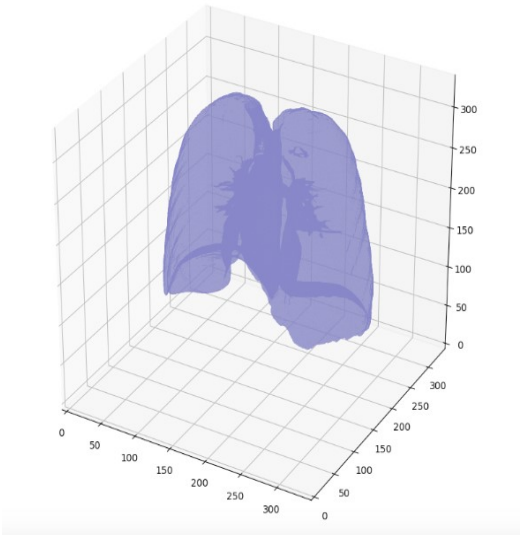

Fig. 5. Segmented pulmonary region

The final steps involved normalizing and zero centring the scans for better homogeneity. The threshold used to normalize was between -1000 and 400. Anything that comes above 400, have not been taken into account as these are the bones with different radio density.

VI. Feature Extraction & Malignancy Detection

The preprocessed dataset was heavily imbalanced at a 1:1000 ratio for nodules and non-nodules correspondingly. Using heavy translations and 3D flips, the dataset was upsampled to a ratio of 1:20. The feature extractor used for the prediction of malignant lung nodules was built using a C3D-based architecture with slight adjustments[18]. The initial model was pre-trained using 800 patient scans and achieved a sensitivity of 76 percent in the FROC analysis. This model was further trained using 65000 advanced preprocessed images derived from the CT scans of 200 more patients. The learning rate was reduced to 0.0001 for the first five iterations and 1e-5 for the next ten. The C3D architecture used as the extractor is a modified version of BVLC Caffe to support 3-Dimensional Convolutional Networks. C3D can be used to train, test, or fine-tune 3D ConvNets efficiently [19]. Table I shows the network architecture of the classifier used.

The malignancy labels from the metadata ranged from 1 (likely not malignant) to 5 (likely malignant). This data was used to train a malignancy estimator along with the classifier using the same architecture.

The approach to use multi-tasked learning for training both the malignancy estimator and the nodule detector using the same neural network gives accurate results [18]. The data was trained using a 32x32x32mm receptive field.

TABLE I
NETWORK ARCHITECTURE

Layer	Parameters	Activation	Output
Inputs			32x32x32, 1
AveragePooling3D	2x1x1		16x32x32, 1
Convolution3D	3x3x3	relu	16x32x32, 64
MaxPooling3D	1x2x2		16x16x16, 64
Convolution3D	3x3x3	relu	16x16x16,128
MaxPooling3D	2x2x2		8x8x8, 128
Convolution3D(2x)	3x3x3	relu	8x8x8, 256
MaxPooling3D	2x2x2		4x4x4, 256
Convolution3D(2x)	3x3x3	relu	4x4x4, 512
MaxPooling3D	2x2x2		2x2x2, 512
Convolution3D (Bottleneck)	2x2x2	relu	1x1x1, 64
Convolution3D (Nodule detector)	2x2x2	sigmoid	1x1x1, 1
Convolution3D (Malignancy Predictor)	2x2x2	none	1x1x1, 1

VII. Result

After training the model and minimizing the loss function using stochastic gradient descent (SGD), the final model was rendered to pinpoint the coordinates of malignant nodules, predict the probability of it being malignant and estimate its malignancy.

The images were resized to 0.5, 0.75, 1.5, and 2 times its size for better prediction of the nodules. The pipeline was then adjusted to let the network predict at these scales. This approach increased the sensitivity of about 3 percent more than the predictions done on a normal scale to 86 percent. The increase in sensitivity occurred as larger and smaller than usual nodules were pinpointed by the network during prediction when the images were scaled to smaller and bigger sizes respectively. The coordinates for the malignant lung nodules are identified using the network and printed to a CSV file and the estimated malignancy scores between 1 and 5 are also estimated and printed correspondingly. The repeated predictions of nodules when the scans were iterated multiple times are then eliminated. The predicted coordinates are demarcated from different slices of the scan and produced as png images.

TABLE II
SENSITIVITIES OBTAINED AFTER DIFFERENT STAGES

Stage	Sensitivity
Initial pre-trained C3D network	76%
After additionally training the C3D network with 200 more patient images	83%
Resized images for prediction	86%

The model is evaluated by detecting its sensitivity using free receiver operating characteristic (FROC) analysis. The hit criterium is that the coordinates of the prediction should be situated at a certain defined distance X from the centre of the actual Nodule, where X is defined as the radius of the nodule, and the sensitivity per scan is determined.

The concluding sensitivity is taken as a mean of seven pre-defined rates of false-positivity 0.125, 0.25, 0.5, 1, 2, 4, and 8 false positives per case [11]. The most desirable score is 1 and the least is 0. The initial pre-trained model had acquired sensitivity of only 0.76 in the FROC analysis. After training it further with better-preprocessed images and tweaking the approach for prediction, the sensitivity was raised to 0.86 for the model. Once the coordinates are predicted and their malignancies estimated, the corresponding images of the nodules based on their locations are generated. Given in Table II are the sensitivities obtained after different stages.

VIII. Conclusion

This paper proposes an approach to improve upon the previous attempts to detect the likely cancerous lung nodules, estimate its probability and malignancy. The automatic detection of malignant lung nodules using DCNN helps radiologists identify malignant nodules that may be overlooked. Our attempt using the C3D architecture has increased the sensitivity of Malignant Lung Nodule Detection to 86 percent, which is 10 percent more than the previous effort at it. This progress was achieved through advanced preprocessing, additional training and better prediction techniques.

References

[1] Lung Cancer 101, lungcancer.org, a program of cancer-care
[2] Ping An Technology (Shenzhen) Co, Pvt Ltd: 3D CNN for Lung Nodule Detection and False Positive Reduction
[3] Deep Learning for Lung Cancer Detection: Tackling the Kaggle Data Science Bowl 2017 Challenge
[4] Jelo Salomon, Bianca Schoen Phelan; Lung Cancer Detection using Deep Convolutional Network (April 2018)
[5] A.A.A. Setio, A. Traverso, T. Bel, et al. Validation, comparison, and combination of algorithms for automatic detection of pulmonary nodules in computed tomography images: the luna16 challenge. In *arXiv:1612.08012*, 2016
[6] Sidharth Bhatia, Yash Sinha, and Lavika Goel: Lung Cancer Detection: A Deep Learning Approach, *SocProS* 2017
[7] Aberle, D.R., Adams, A.M., Berg, C.D., Black, W.C., Clapp, J.D., Fagerstrom, R.M., Ga-reen, I.F., Gatsonis, C., Marcus, P.M., Sicks, J.D.: Reduced lung-cancer mortality with low-dose computed tomographic screening. *N. Engl. J. Med.* ***365****, 395–409* (2011)
[8] S. Sasikala, M. Bharathi, B. R. Sowmiya: Lung Cancer Detection and Classification Using Deep CNN (December 2018), *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*
[9] Thomas HEENEMAN, Dr Mark HOOGENDOORN: Lung nodule detection by using Deep Learning (January 2018)
[10] Nasarullah Nasarullah, Jun Sang, Mohammad S. Alam, Muhammed Mateen, Bin Cai, and Haibo Hu: Automated Lung Nodule Detection and Classification Using Deep Learning Combined with Multiple Strategies (August 2019), *Sensors2019*
[11] Lung Nodule Analysis (LUNA) Challenge. https://luna16.grand-challenge.org/description/
[12] Zatloukal, P., et al.: Concurrent versus sequential chemoradiotherapy with cisplatin and vinorelbine in locally advanced non-small cell lung cancer: a randomized study. *Lung Cancer 46(1) 87–98* (2004)
[13] Kaggle Data Science Bowl 2017. https://www.kaggle.com/c/data-science-bowl-2017
[14] Dev C, Kumar K, Palathil A, Anjali T, Panicker V: Machine Learning-Based Approach for Detection of Lung Cancer in DICOM CT Image (August 2018), *RACCCS* 2018
[15] Sathyan H, Panicker J.V: Lung Nodule Classification Using Deep Convolution Using Deep ConvNets on CT Images (October 2018), *ICCNT* 2018
[16] LIDC-IDRI-The Cancer Imaging Archive (TCIA) Public Access-Cancer Imaging Archive
[17] Guido Zuidhof: https://www.kaggle.com/gzuidhof/full-preprocessing-tutorial
[18] Julian de Wit: http://juliandewit.github.io/kaggle-ndsb2017/
[19] C3D: Generic Features for Video Analysis - http://vlg.cs.dartmouth.edu/c3d/