Lung Cancer Detection Using Convolutional Neural Network

Kavin Selvan V
Rathinam College of arts and science
Coimbatore,India

Venkat Murali K
Rathinam College of arts and science
Coimbatore,India

Imath Rakshan A
Rathinam College of arts and science
Coimbatore,India

***Abstract*—Lung Cancer is one of the leading life taking cancer worldwide. Early detection and treatment are crucial for patient recovery. Medical professionals use histopathological images of biopsied tissue from potentially infected areas of lungs for diagnosis. Most of the time, the diagnosis regarding the types of lung cancer is error-prone and time-consuming. Convolutional Neural networks can identify and classify lung cancer types with greater accuracy in a shorter period, which is crucial for determining patients' right treatment procedure and their survival rate. Benign tissue, Adenocarcinoma, and squamous cell carcinoma are considered in this research work. The CNN model training and validation accuracy of 93.2 and 94.1 percentage are obtained.**

I. INTRODUCTION

Lung cancer is one of the most common cancers, ac- counting for over 225,000 cases, 150,000 deaths, and $12 billion in health care costs yearly in the U.S. [1]. It is alsoone of the deadliest cancers; overall, only 17% of people inthe U.S. diagnosed with lung cancer survive five years after the diagnosis, and the survival rate is lower in developing countries. The stage of a cancer refers to how extensively it has metastasized. Stages 1 and 2 refer to cancers localized to the lungs and latter stages refer to cancers that have spreadto other organs. Current diagnostic methods include biopsies and imaging, such as MRI scans. Early detection of lung cancer (detection during the earlier stages) significantly improves the chances for survival, but it is also more difficult to detect early stages of lung cancer as there are fewer symptoms [1].

Our task is a binary classification problem to detect the presence of lung cancer in patient MRI scans of lungs with and without early stage lung cancer. We aim to use methods from computer vision and deep learning, particularly 2D and 3D convolutional neural networks, to build an accurate classifier. An accurate lung cancer classifier could speed up and reduce costs of lung cancer screening, allowing for more widespread patient classification.

Though this task seems straightforward, it is actually a needle in the haystack problem. In order to determine whether or not a patient has early-stage cancer, the CAD system would have to detect the presence of a tiny nodule (< 10 mm in diameter for early stage cancers) from a large 3D lung scan (typically around 200 mm 400 mm 400 mm). An example of an early stage lung cancer nodule shown in withina MRI 2D slice of a MRI scan is given in Fig. 1. Furthermore, MRI scan is filled with noise from surrounding tissues, bone,air, so for the CAD systems search to be efficient, this noise would first have to be pre-processed. Hence our classification pipeline is image pre-processing, nodule candidates detection, malignancy classification.

II. RELATED WORK

Recently, deep artificial neural networks have been ap-plied in many applications in pattern recognition and machine learning, especially, Convolutional neural networks (CNNs) which is one class of models [3]. Another approach of CNNs was applied on ImageNet Classification in 2012 is called an ensemble CNNs which outperformed the best results which were popular in the computer vision community [4]. There has also been popular latest research in the area of medical imaging using deep learning with promising results.

Suk et al. [5] suggested a new latent and shared feature representation of neuro-imaging data of brain using Deep Boltzmann Machine (DBM) for AD/MCI diagnosis. Wu et al.

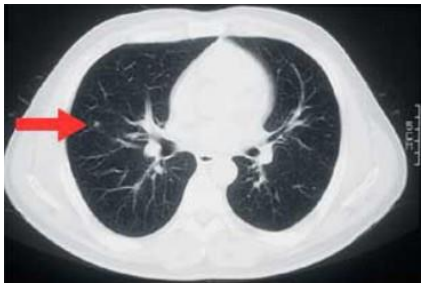

Figure 1: 3D MRI scan slice containing Cancer

Developed deep feature learning for deformable registrationof brain MR images to improve image registration by using deep features. Xu et al. [7] presented the effectiveness of using deep neural networks (DNNs) for feature extraction in medical image analysis as a supervised approach. Kumar etal. [8] proposed a CAD system which uses deep features extracted from an autoencoder to classify lung nodules as either malignant or benign on LIDC database. In [9], Yanivet al. presented a system for medical application of chest pathology detection in x-rays which uses convolutional neural networks that are learned from a non-medical archive. that work showed a combination of deep learning (Decaf) and Pi Codes features achieves the best performance. The proposed combination presented the feasibility of detecting pathologyin chest x-ray using deep learning approaches based on non- medical learning. The used database was composed of 93 images. They obtained an area under curve (AUC) of 0.93 for Right Pleural Effusion

detection, 0.89 for Enlarged heart detection and 0.79 for classification between healthy and abnormal chest x-ray.

In [10], Suna W. et al., implemented three different deep learning algorithms, Convolutional Neural Network (CNN), Deep Belief Networks (DBNs), Stacked Denoising Auto encoder (SDAE), and compared them with the traditional image feature based CAD system. The CNN architecture contains eight layers of convolutional and pooling layers, interchangeably. For the traditional compared to algorithm, there were about 35 extracted texture and morphological features. These features were fed to the kernel based support vector machine (SVM) for training and classification. The resulted accuracy forthe CNN approach reached 0.7976 which was little higher thanthe traditional SVM, with 0.7940. They used the Lung Image Database Consortium and Image Database Resource Initiative (LIDC/IDRI) public databases, with about 1018 lung cases.

In [11], J. Tan et al. designed a framework that detected lung nodules, then reduced the false positive for the detected nodules based on Deep neural network and Convolutional Neural Network. The CNN has four convolutional layers and four pooling layers. The filter was of depth 32 and size 3,5. The used dataset was acquired from the LIDC-IDRI for about 85 patients. The resulted sensitivity was of 0.82. The False positive reduction gotten by DNN was 0.329.

In [12], R. Golan proposed a framework that train the weights of the CNN by a back propagation to detect lung nodules in the CT image sub-volumes. This system achieved sensitivity of 78.9% with 20 false positives, while 71.2% with 10 FPs per scan, on lung nodules that have been annotated by all four radiologists

Convolutional neural networks have achieved better than Deep Belief Networks in current studies on benchmark computer vision datasets. The CNNs have attracted considerable interest in machine learning since they have strong Representation ability in learning useful features from input data in recentyears

III.DATA

Our primary dataset is the patient lung MRI scan dataset from TCIA. The dataset contains labelled data for 1397 patients, which we divide into training set of size 978, and test set of size 419. For each patient, the data consists of MRI scan data and a label (0 forno cancer, 1 for cancer).. For each patient, the MRI scan data consists of a variable number of images (typically around 100-400, each image is an axial slice) of 512 512 pixels. The slices are provided in DICOM format. Around 70% of the provided labels in the TCIA are 0, so we used a weighted loss function in our malignancy classifier to address this imbalance.

Because the alone proved to be inadequate to accurately classify the validation set, we also used the patient lung MRI scan dataset with labelled nodules from the Lung Nodule Analysis [14] totrain a U-Net for lung nodule detection. The TCIA dataset contains labelled data for 888 patients, which we divided intoa training set of size 710 and a validation set of size 178. For each patient, the data consists of MRI scan data and a nodule label (list of nodule Center coordinates and diameter). For eachpatient, the MRI scan data consists of a variable number of images (typically around 100-400, each image is an axial slice)of 512 × 512 pixels.

IV.METHODS

Typical CAD systems for lung cancer have the following pipeline: image pre-processing, detection of cancerous nodule candidates, nodule candidate false positive reduction, malignancy prediction for each nodule candidate, and malignancy prediction for overall CT scan [15]. These pipelines have many phases, each of which is computationally expensive and requires well-labelled data during training. For example, the false positive reduction phase requires a dataset of labelled true and false nodule candidates, and the nodule malignancy prediction phase requires a dataset with nodules labelled with malignancy.

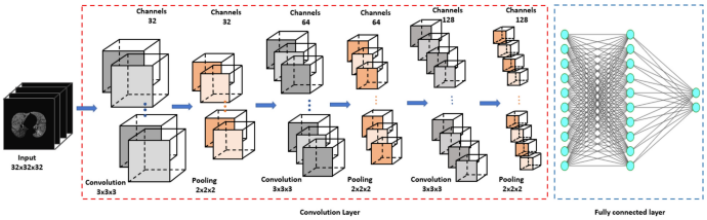

Figure 2: 3D convolutional neural networks architecture.

True/False labels for nodule candidates and malignancy labels for nodules are sparse for lung cancer, and may be non-existent for some other cancers, so CAD systems that rely on such data would not generalize to other cancers. In order to achieve greater computational efficiency and generalizability to other cancers, the proposed CAD system has shorter pipeline and only requires the following data during training: a dataset of CT scans with true nodules labelled, and a dataset of CT scans with an overall malignancy label. State-of-the-art CAD systems that predict malignancy from CT scans achieve AUC of up to 0.83 [16]. However, as mentioned above, these systemstake as input various labelled data that is not used in thisframework. The main goal of the proposed system is to reach close to this performance.

The proposed CAD system starts with pre-processing the 3D CT scans using segmentation, normalization, down sampling, and zero-centring. The initial approach was to simply input the pre-processed 3D CT scans into 3D CNNs, but the results were poor. So an additional pre-processing was performed to input only regions of interests into the 3D CNNs. To identify regions of interest, a U-Net was trained for nodule candidate detection. Then input regions around nodule candidates detected by the U-Net was fed into 3D CNNs to ultimatelyclassify the CT scans as positive or negative for lung

cancer. The overall architecture is shown in Fig. 2, all details of layerswill be described in the next sections.

A. Pre-processing and Segmentation

For each patient, pixel values was first converted in each image to Hounsfield units (HU), a measurement of Radio density, and 2D slices are stacked into a single 3D image. Because tumors form on lung tissue, segmentation is used to mask out the bone, outside air, and other substances that would make data noisy, and leave only lung tissue information for the classifier. A number of segmentation approaches were tried, including thresholding, clustering (Kmeans and Meanshift), and Watershed. K-means and Meanshift allow very little super-vision and did not produce good qualitative results. Watershedproduced the best qualitative results, but took too long to runto use by the deadline. Ultimately, thresholding was used.

After segmentation, the 3D image is normalized by applying the linear scaling to squeezed all pixels of the original unsegmented image to values between 0 and 1. Spline interpolation down samples each 3D image by a scale of 0.5 in each of the three dimensions. Finally, zero centering is performed on data by subtracting the mean of all the images from the training set.

1)Thresholding: Typical radiodensities of various parts of a MRI scan are shown in Table I. Air is typically around -1000 HU, lung tissue is typically around -500, water, blood, and other tissues are around 0 HU, and bone is typically around 700HU, so pixels that are close to -1000 or above -320 are masked

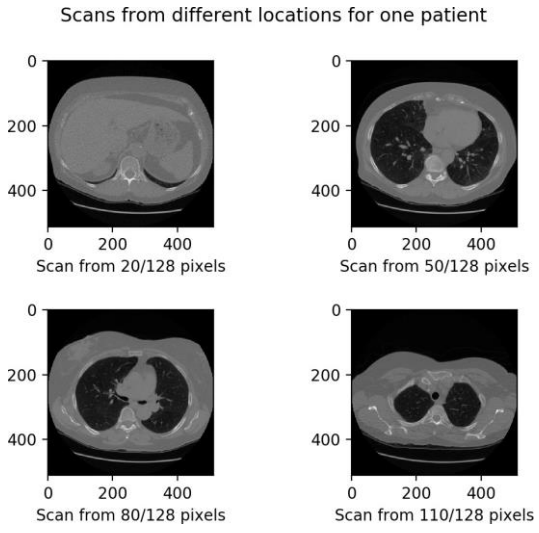

Figure 3 Corresponding axialslices for sample patient 3D image at various axial.

After segmentation, the 3D image is normalized by applying the linear scaling to squeezed all pixels of the original unsegmented image to values between 0 and 1. Spline interpolation down samples each 3D image by a scale of 0.5 in each of the three dimensions. Finally, zero-centering is performed on data by subtracting the mean of all the images from the training set. After segmentation, we normalize the 3D image by applying the linear scaling to squeezed all pixels of the original unsegmented image to values between 0 and 1.
Then we use spline interpolation to down sample each 3D image by a scale of 0.5 in each of the three dimensions. Finally, we zero-center the data be subtracting the mean of all the images from the training set. 4.1.1 Thresholding Typical radiodensities of various parts of a CT scan are shown in Table 1. Air is typically around −1000 HU, lung tissue is typically around −500, water, blood, and other tissues are around 0 HU, and bone is typically around 700 HU, so we mask out pixels that are close to −1000 or above −320 to leave lung tissue as the only segment.

V. 3D CNN ARCHITECTURE

Feeding the entire segmented lungs into malignancy classifiers made results very poor. It was likely the case that the entire image was too large search space. Thus feeding smaller regions of interest instead of the entire segmented 3D image is more convenient. This was achieved by selecting small boxes containing top cancerous nodule candidatesi 2D CNN architecture that is popular for biomedical image segmentation. A stripped-down version of the U-Net is designed to limit memory expense. A visualization of the and is described in detail, during training, the modified U-Net takes as input 2D CT slices, and labels are provided mask where nodule pixels are 1, rest are 0). The model is trained to output images of shape where each pixel of the output has a value between 0 and 1 indicating the probability the pixel belongs to a nodule.

.

VI. 3D CNN CLASSIFIERS

Once the CNN was trained on the data, it is ran on stacked the 2D slices backto generate nodule candidates [1]. Ideally the output of CNN would give the exact locations of all the nodules, and it would be able to declare images with nodules as detected by U-Net are positive for lung cancer, and images without any nodules detected by CNNare negative for lung cancer. However, as shown in, CNNproduces a strong signal for the actualnodule, but also produces a lot of false positives, so we needan additional classifier that determines, .Because CNN generates more suspicious regions than actual nodules, the top 8 nodule candidates are located (32 32 32 *volumes*) by sliding a window over the data and saving the locations of the 8 most activated (largest L2 norm) sectors.To prevent the top sectors from simply being clustered in the brightest region of the image, the 8 sectors were not permitted to overlap with each other. An example architecture of a 3D convolutional neuralnetwork used here. On the left is the input 3D volume, followedby two convolutional layers, a fully connected layers

and an output layer. In the convolutional layers, each filter (or channel)is represented by a volume.

VII. RESULTS AND DISCUSSIONS

The model is being trained with the epoch value as 50. Training for a higher epoch value allows the model to adjust its weights and biases to detect more subtle featuresof lung cancer. This increases the sensitivity of the modeland enables it to detect cancers that may have gone unnoticed in earlier models. It can lead to improved patientoutcomes, by providing earlier detection of Lung cancer and enabling earlier interventions, leading to better prognosis and survival rates for patient

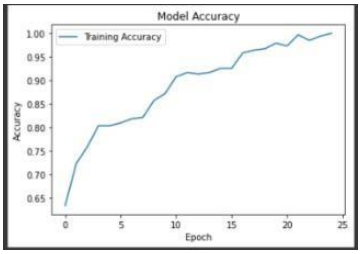

Figure 4: Model loss graph (Epoch value 50)

The model is being trained with the epoch value as 50..A longer training time allows the model to learn andanalyze from a larger set of brain images, which improves itsaccuracy and sensitivity in detecting cancer. Training a lung cancer model with an epoch value of 50 provides a more reliable and accurate tool for diagnosing and treating lung cancer, thereby improving patient outcomes.

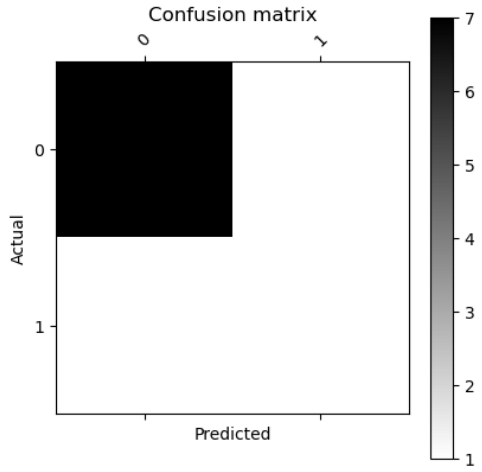

Figure 5: A Confusion Matrix of the trained model

A confusion matrix of the CNN trained on 90% (360 images) of the dataset and tested on the remaining 10% (images). Rows represent the actual classes of an image. Columns represent the CNN's class prediction. Each cell in the matrix represents the percentage of images of the row's class that were classified to the column's class.

VIII. REFERENCES

[1] W.-J. Choi and T.-S. Choi, "Automated pulmonary nodule detection system in computed tomography images: A hierarchical block classifi- cation approach," *Entropy*, vol. 15, no. 2, pp. 507–523, 2013.

[2] A. Chon, N. Balachandar, and P. Lu, "Deep convolutional neural networks for lung cancer detection," tech. rep., Stanford 2017.

[3] Y. LeCun, K. Kavukcuoglu, and C. Farabet, "Convolutional networks and applications in vision.," in *Proceedings of the IEEE International Symposium on Circuits and Systems (ISCAS)*, pp. 253–256, IEEE, 2010.

[4] K. Alex, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in Neural InformationProcessing Systems 25 (NIPS 2012)* (F. Pereira, C. J. C. Burges,
L. Bottou, and K. Q. Weinberger, eds.), pp. 1097–1105, 2012.

[5] H. Suk, S. Lee, and D. Shen, "Hierarchical feature representation and multimodal fusion with deep learning for AD/MCI diagnosis," *NeuroImage*, vol. 101, pp. 569–582, 2014.

[6] G. Wu, M. Kim, Q. Wang, Y. Gao, S. Liao, and D. Shen, "Unsupervised deep feature learning for deformable registration of mr brain images.," *Medical Image Computing and Computer-Assisted Intervention*, vol. 16,no. Pt 2, pp. 649–656, 2013.

[7] Y. Xu, T. Mo, Q. Feng, P. Zhong, M. Lai, and E. I. Chang, "Deep learn-ing of feature representation with multiple instance learning for medical image analysis," in *IEEE International Conference on Acoustics, Speechand Signal Processing, ICASSP*, pp. 1626–1630, 2014.

[8] D. Kumar, A. Wong, and D. A. Clausi, "Lung nodule classification using deep features in ct images," in *2015 12th Conference on Computer and Robot Vision*, pp. 133–138, June 2015.

[9] Y. Bar, I. Diamant, L. Wolf, S. Lieberman, E. Konen, and H. Greenspan, "Chest pathology detection using deep learning with non-medical train-ing," *Proceedings - International Symposium on Biomedical Imaging*, vol. 2015-July, pp. 294–297, 2015.

[10] W. Sun, B. Zheng, and W. Qian, "Computer aided lung cancer diagnosiswith deep learning algorithms," in *SPIE Medical Imaging*, vol. 9785, pp. 97850Z–97850Z, International Society for Optics and Photonics, 2016.

[11] J. Tan, Y. Huo, Z. Liang, and L. Li, "A comparison study on the effect of false positive reduction in deep learning based detection for juxtapleural lung nodules: Cnn vs dnn," in *Proceedings of the Symposium on Modeling and Simulation in Medicine*, MSM '17, (San Diego, CA, USA), pp. 8:1–8:8, Society for Computer Simulation International, 2017.

[12] R. Golan, C. Jacob, and J. Denzinger, "Lung nodule detection in ct im- ages using deep convolutional neural networks," in *2016 International Joint Conference on Neural Networks (IJCNN)*, pp. 243–250, July 2016.

[13] Kaggle, "Data science bowl 2017." https://www.kaggle.com/c/data-science-bowl-2017/data, 2017.

[14] LUNA16, "Lung nodule analysis 2016." https://luna16.grand-challenge.org/, 2017.

[15] M. Firmino, A. Morais, R. Mendoa, M. Dantas, H. Hekis, and R. Valentim, "Computer-aided detection system for lung cancer in computed tomography scans: Review and future prospects," *BioMedicalEngineering OnLine*, vol. 13, p. 41, 2014.

[16] S. Hawkins, H. Wang, Y. Liu, A. Garcia, O. Stringfield, H. Krewer,
Q. Li, D. Cherezov, R. A. Gatenby, Y. Balagurunathan, D. Goldgof,
M. B. Schabath, L. Hall, and R. J. Gillies, "Predicting malignant nodulesfrom screening ct scans," *Journal of Thoracic Oncology*, vol. 11, no. 12,pp. 2120–2128, 2016.

[17] M. S. AL-TARAWNEH, "Lung cancer detection using image processingtechniques," *Leonardo Electronic Journal of Practices and Technolo- gies*, pp. 147–158, June 2012.

[18] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional net-works for biomedical image segmentation," *CoRR*, vol. 18