Section A-Research paper
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Semi-Supervised Deep Transfer Learning for Benign-Malignant Diagnosis of Pulmonary Nodules in Chest CT Images

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ABSTRACT: Lung cancer is the main cause of mortality from cancer globally. It is critical in clinical practise to correctly diagnose the malignancy of suspected lung nodules. However, the pathologically established lung nodule dataset is still substantially restricted and significantly uneven in benign and malignant distributions. In this article, we introduced a Semi-supervised Deep Transfer Learning (SDTL) system for distinguishing benign from malignant lung nodules. First, we apply a transfer learning technique with a pre-trained classification network to distinguish lung nodules from nodule-like tissues. Second, since the number of pathologically proved samples is limited, an iterated feature-matching-based semi-supervised technique is developed to take use of a large accessible dataset with no pathological findings. To iteratively enhance the classification network, a similarity metric function is used in the network semantic representation space to progressively include a small fraction of examples with no abnormal outcomes. In this investigation, 3,038 pulmonary nodules with pathologically proved benign or malignant labels (from 2,853 people) and 14,735 unlabeled lesions (from 4,391 participants) were gathered retrospectively. Our proposed SDTL framework exhibits higher diagnostic performance in the main dataset, with accuracy = 88.3%, AUC = 91.0%, and accuracy = 74.5%, AUC = 79.5% in the independent testing dataset. Furthermore, an ablation research reveals that using transfer learning improves accuracy by 2%, while using semi-supervised learning improves accuracy by 2.9%. The findings suggest that our proposed classification network might be an excellent diagnostic tool for suspected lung nodules and could have a potential clinical use.

Keywords *– Pulmonary nodule, deep learning, transfer learning, semi-supervised learning, benign-malignant classification.*

1. INTRODUCTION

Because of its aggressive nature and late identification at advanced stages, lung cancer remains the largest cause of tumor-associated death [1]. According to the Global Cancer Observatory (GLOBOCAN) 2018 estimates of incidence and mortality globally for 36 cancers in 185 countries in 2018, lung cancer accounts for roughly 1.8 million fatalities (i.e., over 9.6 million cancer deaths recorded in 2018) [2]. As a result, early identification of malignant lung nodules is critical in lung cancer diagnosis. Pathology is largely considered as the gold standard for determining whether lung nodules are benign or malignant. Histopathology and molecular biology conducted on tissue specimens (e.g., surgical resection and needle biopsy) are the standards for pathological identification of nodules in clinical practise, although they are invasive and time-consuming. CT scan, on the other hand, as a non-invasive approach, enables further diagnostic and staging of pulmonary nodules, especially in high-risk patients [3], [4]. However, distinguishing malignant pulmonary nodules from benign ones using CT morphological characteristics alone remains difficult, since it typically relies heavily on radiologists' knowledge and is error-prone in the case of identifying and interpreting tiny nodules [5]. Figure 1 depicts ten benign and ten cancerous nodules. As seen in Fig. 1A, some benign nodules may exhibit malignant-like traits (e.g., lobulated and spiculated margins) that are visually similar to malignant nodules. Furthermore, the tiny nodules indicated by arrows in Fig. 1B show as solids on the CT scan, which is comparable to benign nodules. Furthermore, manual reading may miss some pulmonary nodules owing to radiologists' errors due to weariness in a high workload state or low picture quality [6], [7]. As a result, developing a computer-aided strategy to automatically identify pulmonary nodules and objectively discriminate malignant nodules from benign nodules in chest CT scans is very desired.

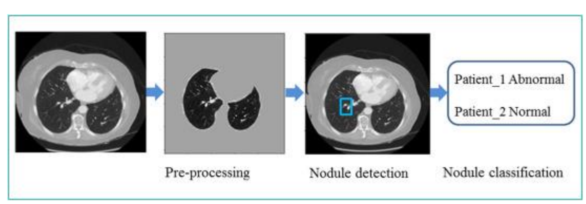

Fig.1: Example figure

Machine learning algorithms have been proposed to automatically interpret CT images and provide recommended boxes for pulmonary nodules as well as their anticipated benign or malignant statuses to make the procedure of pulmonary nodule identification more realistic [5]. Recent deep learning approaches, in particular, with the capacity to learn mid- and high-level visual representations [8], have seen broad application in the distinction of malignant pulmonary nodules from benign ones. Sun et al. [9] utilised the Lung Image Database Consortium (LIDC) database, which had 1018 lung CT cases with benign or malignant classifications supplied by four radiologists for each nodule, and Deep Belief Networks (DBNs) for lung cancer detection. When compared to the standard machine learning model, which had 79.4% accuracy, the support vector machine produced an excellent discriminate performance with 81.2% accuracy.

2. LITERATURE REVIEW

Lung cancer identification: A review on detection and classification:

Lung cancer is one of the most frequent illnesses in humans and one of the leading causes of death. Medical experts think that detecting lung cancer in its early stages with computed tomography (CT) screening may minimise mortality. Examining a large number of CT scans may help to lessen the danger. However, CT scan pictures provide a huge amount of information concerning nodules, and the rising quantity of images makes correct evaluation difficult for radiologists. To aid radiologists, new approaches based on handicraft and learning methodology have recently emerged. In this study, we analysed many potential ways established in the computer-aided diagnosis (CAD) system to identify and categorise nodules using CT image analysis to help radiologists and give a detailed analysis of diverse methodologies.

A review of lung cancer screening and the role of computer-aided detection:

Lung cancer is the biggest cause of cancer-related mortality globally; nevertheless, early detection leads to a better chance of survival. The National Lung Screening Trial (NLST) found that scanning with low-dose computed tomography (LDCT) reduced mortality by 20% in a high-risk cohort. This study discusses current improvements in screening eligibility criteria, as well as the potential advantages and drawbacks of CT screening. Computer-aided detection (CAD) has been used to assist radiologists in lung nodule identification to make the screening procedure more practicable and to help lower the percentage of missed lung nodules. The purpose of this study is to go through how CAD works, how well it detects lung nodules, and what variables impact its effectiveness. The purpose of this article is also to explore the influence of various forms of CAD on CT in lung nodule identification, as well as the effect of CAD on radiologists' decision outcomes.

Impact of a computer-aided detection (CAD) system integrated into a picture archiving and communication system (PACS) on reader sensitivity and efficiency for the detection of lung nodules in thoracic CT exams:

The goal of this research is to evaluate the influence of a computer-aided detection (CAD) device seamlessly incorporated into a commercially available photo archiving and communication system on nodule identification and efficiency (PACS). From an ongoing multi-institutional screening investigation, 48 consecutive low-dose thoracic computed tomography examinations were included retrospectively. For each research, CAD data were submitted to PACS as a single picture series. Five fellowship-trained thoracic radiologists examined the CAD output series after initially interpreting each case on contiguous 5 mm sections (with CAD marks on corresponding axial sections). The reference standard was based on three-reader agreement with expert adjudication. The amount of time it took to interpret CAD marking was automatically recorded. Our research comprised 134 true-positive nodules measuring 3 mm or bigger, with 85 4 and 50 5 mm in size. When employing CAD, reader detection increased dramatically in each size category, from 44 to 57% for 3 mm, 48 to 61% for 4 mm, and 44 to 60% for 5 mm. The CAD stand-alone sensitivity for nodules 3, 4, and 5 mm, respectively, was 65, 68, and 66%, with CAD considerably raising false positives for two readers alone. After localising a CAD mark in the original picture series, the average time to analyse and annotate it was 15.1 seconds. The incorporation of CAD into PACS improves reader sensitivity while reducing interpretation time, and it encourages such application in regular clinical practise.

Computer-aided detection of lung nodules on multidetector CT in concurrent-reader and second-reader modes: A comparative study:

To compare the reading times and detection performances of radiologists using computer-aided detection (CAD) for lung nodules on multidetector computed tomography in concurrent-reader and second-reader modes (CT). Materials and procedures: Fifty clinical multidetector CT datasets with nodules up to 20mm in diameter were gathered retrospectively.

Six radiologists (3 experienced radiologists and 3 resident radiologists) independently assessed these datasets twice for the identification and grading of non-calcified nodules bigger than 4mm in diameter, once with concurrent-reader CAD and once with second-reader CAD. The agreement of two experienced chest radiologists was used to define the reference standard of nodules in the datasets. The reading durations and detection performances in the two modes of CAD were statistically evaluated, with the detection performances compared using jackknife free-response receiver operating characteristic (JAFROC) analysis. The reference standard consisted of two hundred and seven nodules. The mean reading time for the six radiologists was 132s with concurrent-reader CAD and 210s with second-reader CAD (p0.01). JAFROC analysis found no significant difference in detection performance between the two modes, with the 6 radiologists' average figure-of-merit value being 0.70 with concurrent-reader CAD and 0.72 with second-reader CAD (p=0.35). Conclusion: In multidetector CT CAD for lung nodules, the concurrent-reader mode is more time-efficient than the second-reader approach, and there is no significant difference in radiologists' detection performance between the two modalities.

Computer-assisted decision support system in pulmonary cancer detection and stage classification on CT images:

Pulmonary cancer is one of the leading causes of mortality globally. Computer-assisted diagnosis (CADx) tools have been developed to identify lung cancer. The Online of Things (IoT) has provided ubiquitous internet access to biomedical information and methodologies, resulting in substantial advancement in CADx. Deep learning approaches, as opposed to traditional CADx, provide the fundamental benefit of an automated exploitation feature since they can learn mid and high level picture representations. We suggested a Computer-Assisted Decision Support System in Pulmonary Cancer employing a new deep learning-based model with MBAN metastatic data (Medical Body Area Network). DFCNet, the suggested model, is based on the deep fully convolutional neural network (FCNN), which is utilised to classify each identified pulmonary nodule into four stages of lung cancer. The suggested work's performance is assessed on several datasets with changing scan circumstances. The suggested classifier is compared against current CNN approaches. CNN and DFCNet had overall accuracy of 77.6% and 84.58%, respectively. The experimental findings demonstrate the efficacy of the suggested strategy for detecting and classifying lung cancer nodules. These findings show that the suggested approach has the potential to assist radiologists in boosting nodule detection accuracy while remaining efficient.

3. METHODOLOGY

Building cutting-edge deep learning models often needs a huge number of annotated training pictures in order to learn millions of parameters. Preparing such training datasets remains a significant problem in the medical arena, since getting high-quality data labels is time-consuming and expensive. Transfer learning, a common deep learning optimization strategy for limited datasets, has been implemented in pulmonary nodule classification and demonstrates outstanding results. Xie and his colleague, for example, presented a Multi-View Knowledge-Based Collaborative (MV-KBC) deep model, using transferable ResNet-50 networks, to diagnose benign-malignant nodules with little data and obtained 91.6% accuracy. Their transfer learning technique, however, is based on non-medical pictures (i.e., the ImageNet dataset), which may restrict the performance of the medical image domain. Shen et al. suggested a domain-adaptation method for predicting nodule malignancy using transferable CNN-based features learned from 2272 nodules without pathologically validated annotations. The model's performance was increased from 65.4% to 70.7% using the medical-to-medical transfer learning approach.

Disadvantages:

1. Because collecting high-quality data labels is time-consuming and expensive.
2. Insufficient data

We presented a new approach to address the difficult challenge of distinguishing malignant pulmonary nodules from benign nodules in chest CT images. We devised an unique semi-supervised deep transfer learning approach, employing both labelled and unlabeled nodules, to successfully address the problem of inadequate dataset. Experiment findings suggest that our proposed strategy outperforms state-of-the-art methods and has the potential to increase generalizability. Ablation experiments are used to validate the efficacy of the two suggested techniques, medical-to-medical transfer learning and iterative featurematching-based semi-supervised learning. Although our present model was designed for pulmonary nodule identification, it may be adapted to various medical applications.

Advantages:

1. Our proposed classification network might be an excellent diagnostic tool for suspected lung nodules and could have a potential clinical use.

2. According to an ablation research, using transfer learning improves accuracy by 2%, while using semi-supervised learning improves accuracy by 2.9%.

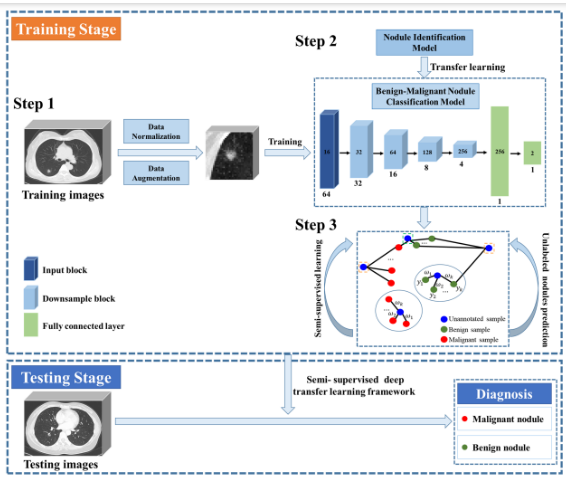

Fig.2: System architecture

MODULES:

To carry out the aforementioned project, we created the modules listed below.

- Data exploration: we will put data into the system using this module.
- Processing: we will read data for processing using this module.
- Splitting data into train and test: Using this module, data will be separated into train and test models.
- Making the model - Baseline Model - Resnet50 backbone - Baseline + TL - InceptionV3 backbone - Baseline + SDTL - Inception backbone ResNetV2, MobileNet, and DenseNet are three types of networks. Calculated algorithm accuracy
- User registration and login: Using this module will result in registration and login.
- User input: Using this module will provide input for prediction
- Prediction: the final projected value will be presented

4. IMPLEMENTATION

ALGORITHMS:

Resnet50's Baseline Model: A baseline model is simply a simple model that serves as a reference in a machine learning project. Its primary role is to contextualise trained model findings. Baseline models are often simple and have little predictive value. Regardless, their participation is essential for a variety of reasons.

ResNet50 is a ResNet model version having 48 Convolution layers, 1 MaxPool layer, and 1 Average Pool layer. It can do 3.8 x 109 floating point computations. It is a popular ResNet model, and we have thoroughly investigated the ResNet50 architecture.

Baseline + TL - backbone of InceptionV3: Inception v3 is an image recognition model that has been found to achieve higher than 78.1% accuracy on the ImageNet dataset using baseline + TL. The model represents the result of several concepts explored over time by many academics.

Baseline + SDTL - the foundation of Inception ResNetV2: ResNetV2 is an Inception-ResNet-v2 convolutional neural network that has been trained on over a million photos from the ImageNet collection [1]. The network has 164 layers and can identify photos into 1000 item categories, including keyboards, mice, pencils, and a variety of animals.

MobileNet: MobileNet is a network model that uses depthwise separable convolution as its main unit. It has two layers in its depthwise separable convolution: depthwise convolution and point convolution.

DenseNet: A DenseNet is a sort of convolutional neural network that makes use of dense connections between layers through Dense Blocks, which link all layers (with matching feature-map sizes) directly with each other. DenseNet was created primarily to address the vanishing gradient-induced loss in accuracy in high-level neural networks. In plain words, the information evaporates before reaching its destination owing to the longer journey between the input layer and the output layer.

5. EXPERIMENTAL RESULTS

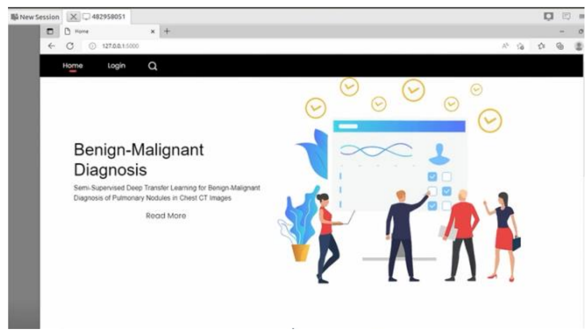

Fig.3: Home screen

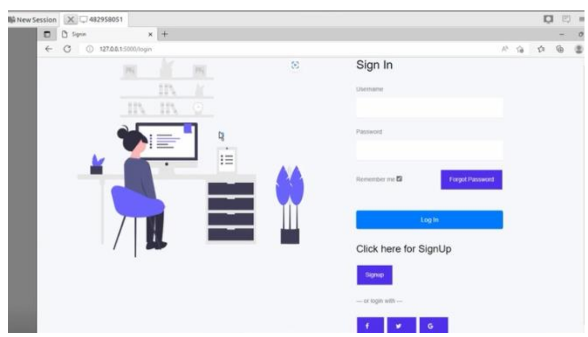

Fig.4: User signin

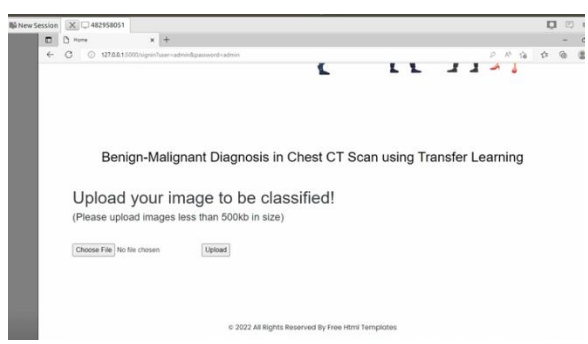

Fig.5: Main page

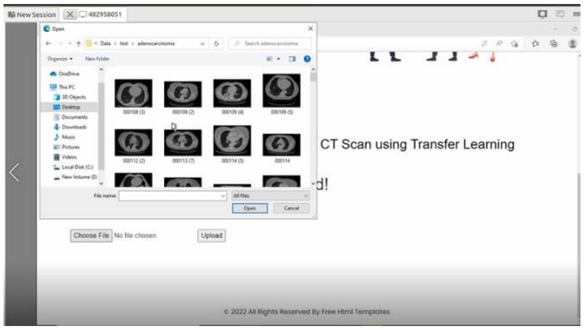

Fig.6: User input

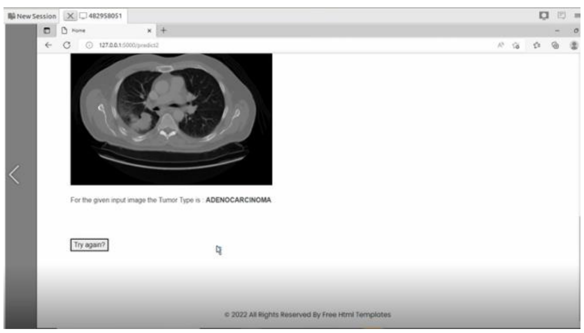

Fig.7: Prediction result

6. CONCLUSION

We presented a new approach to address the difficult challenge of distinguishing malignant pulmonary nodules from benign nodules in chest CT images. We devised a unique semi-supervised deep transfer learning approach, employing both labelled and unlabeled nodules, to successfully address the problem of inadequate dataset. Experiment findings suggest that our proposed strategy outperforms state-of-the-art methods and has the potential to increase generalizability. Ablation experiments are used to validate the efficacy of the two suggested techniques, medical-to-medical transfer learning and iterative featurematching-based semi-supervised learning. Although our present model was designed for pulmonary nodule identification, it may be adapted to various medical applications.

REFERENCES

[1] R. L. Siegel, K. D. Miller, and A. Jemal, “Cancer statistics, 2019,” CA, Cancer J. Clin., vol. 69, no. 1, pp. 7–34, 2019.

[2] F. Bray, J. Ferlay, I. Soerjomataram, R. L. Siegel, L. A. Torre, and A. Jemal, “Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries,” CA, Cancer J. Clin., vol. 68, no. 6, pp. 394–424, 2018.

[3] H. Macmahon et al., “Guidelines for management of incidental pulmonary nodules detected on CT images: From the Fleischner society 2017,” Radiology, vol. 284, no. 1, pp. 228–243, Jul. 2017.

[4] S. K. Thakur, D. P. Singh, and J. Choudhary, “Lung cancer identification: A review on detection and classification,” Cancer Metastasis Rev., vol. 39, no. 3, pp. 989–998, Sep. 2020.

[5] B. Al Mohammad, P. C. Brennan, and C. Mello-Thoms, “A review of lung cancer

screening and the role of computer-aided detection," Clin. Radiol., vol. 72, no. 6, pp. 433–442, Jun. 2017.

[6] L. Bogoni et al., "Impact of a computer-aided detection (CAD) system integrated into a picture archiving and communication system (PACS) on reader sensitivity and efficiency for the detection of lung nodules in thoracic CT exams," J. Digit. Imag., vol. 25, no. 6, pp. 771–781, Dec. 2012.

[7] S. Matsumoto et al., "Computer-aided detection of lung nodules on multidetector CT in concurrent-reader and second-reader modes: A comparative study," Eur. J. Radiol., vol. 82, no. 8, pp. 1332–1337, Aug. 2013.

[8] A. Masood et al., "Computer-assisted decision support system in pulmonary cancer detection and stage classification on CT images," J. Biomed. Inf., vol. 79, pp. 117–128, Mar. 2018.

[9] W. Sun, B. Zheng, and W. Qian, "Computer aided lung cancer diagnosis with deep learning algorithms," Proc. SPIE, vol. 9785, Mar. 2016, Art. no. 97850Z.

[10] J. J. Näppi, T. Hironaka, D. Regge, and H. Yoshida, "Deep transfer learning of virtual endoluminal views for the detection of polyps in CT colonography," Proc. SPIE, vol. 9785, Mar. 2016, Art. no. 97852B.