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Medical Image Analysis of Lung Cancer Using DL with SwarmOptimization Techniques

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ABSTRACT:

Medical imaging tools are essential in early-stage lung cancer diagnostics and the monitoring of lung cancer during treatment. Various medical imaging modalities, such as chest X-ray, magnetic resonance imaging, positron emission tomography, computed tomography, and molecular imaging techniques, have been extensively studied for lung cancer detection. These techniques have some limitations, including not classifying cancer images automatically, which is unsuitable for patients with other pathologies. with rapidly emerging applications spanning medical image-based and textural data modalities. With the help of deep learning- based medical imaging tools, clinicians can detect and classify lung nodules more accurately and quickly. This paper presents the recent development of deep learning-based imaging techniques for early lung cancer detection.

KEYWORDS:

lung cancer, medical images, segmentation, classification, deep learning, convolutional neural network.

INTRODUCTION:

Lung cancer is the most frequent cancer and the cause of cancer death, with the highest morbidity and mortality in the United States . In 2018, GLOBOCAN estimated approximately 2.09 million new cases and 1.76 million lung cancer-related deaths . Lung cancer cases and deaths have increased significantly globally . Approximately 85–88% of lung cancer cases are non-small cell lung carcinoma (NSCLS), and about 12–15% of lung cancer cases are small cell lung cancer (SCLC) . Early lung cancer diagnosis and intervention are crucial to increase the overall 5-year survival rate due to the invasiveness and heterogeneity of lung cancer[1] .

Over the past two decades, various medical imaging techniques, such as chest X-ray, positron emission tomography (PET), magnetic resonance imaging (MRI), computed tomography (CT), low-dose CT (LDCT), and chest radiograph (CRG), have been extensively investigated for lung nodule detection. Although CT is the golden standard imaging tool for lung nodule detection, it can only detect apparent lung cancer with high false-positive rates and produces harmful X-ray radiation[2] . LDCT has been proposed to reduce harmful radiation to detect lung cancer . However, cancer-related deaths were concentrated in subjects undergoing LDCT. 2-deoxy-18F-fluorodeoxyglucose (18F-FDG) PET has been developed toimprove the detection performance of lung cancer[3] . 18F-FDG PET produces semi-quantitative parameters of tumor glucose metabolism, which is helpful in the diagnosis of NSCLC . However, 18F-FDG PET requires further evaluation of

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patients with NSCLC [4]. Some new imaging techniques, such as magnetic induction tomography (MIT), have been developed for early-stage cancer cell detection [5]. However, this technique lacks clinical validation of human subjects.

Many computer-aided detection (CAD) systems have been extensively studied for lung cancer detection and classification . Compared to trained radiologists, CAD systems provide better lung nodules and cancer detection performance in medical images [6]. Generally, the CAD-based lung cancer detection system includes four steps: image processing, extraction of the region of interest (ROI), feature selection, and classification. Among these steps, feature selection and classification play the most critical roles in improving the accuracy and sensitivity of the CAD system, which relies on image processing to capture reliable features. However, benign and malignant nodule classification is a challenge [7]. Many investigators have applied deep learning techniques to help radiologists make more accurate diagnoses Previous studies have confirmed that deep learning-based CAD systems can effectively improve the efficiency and accuracy of medical diagnosis, especially for diagnosing various common cancers, such as lung and breast cancers . Deep learning-based CAD systems can automatically extract high-level features from original images using different network structures than traditional CAD systems [8]. However, deep learning-based CAD systems have some limitations, such as low sensitivity, high FP, and time consumption [9]. Therefore, a rapid, cost-effective, and highly sensitive deep learning-based CAD system for lung cancer prediction is urgently needed

EXISTING APPROACH:

Medical imaging tools help radiologists diagnose lung disease. Among these medical imaging approaches, CT offers more advantages, including size, location, characterization, and lesion growth, which could identify lung cancer and nodule information [10]. 4D CT provides more precise targeting of the administered radiation, which significantly impacts lung cancer management . Lakshmanaprabu et al. developed an automatic detection system based on linear discriminate analysis (LDA) and an optimal deep neural network (ODNN) to classify lung cancer in CT lung images. The LDA reduced the extracted image features to minimize the feature dimension [11]. The ODNN was applied and optimized bya modified gravitational search algorithm to provide a more accurate classification result. Compared to CT, LDCT is more sensitive to early-stage lung nodules and cancer detection with reduced radiation. However, it does not help reduce lung cancer mortality. It is recommended that LDCT be carried out annually for high-risk smokers aged 55 to 74 [12].

PET produces much higher sensitivity and specificity for lung nodule detection than CT due to reactive or granulomatous nodal disease[13] . PET offers a good correlation with longer progression times and overall survival rates. 18F-FDG PET has been applied to diagnose solitary pulmonary nodules . 18F-FDG PET is a crucial in-patient selection and advanced NSCLC for radical radiotherapy. PET-assisted radiotherapy offers more accuracy and manages about 32%of patients with stage IIIA lung cancer[14] . 18F-FDG PET provides a significant response assessment in patients with NSCLC undergoing induction chemotherapy.

PROPOSED APPROACH:

This paper presents recent achievements in lung cancer segmentation, detection, and classification using deep learning methods. This study highlights current state-of-the-art deep learning-based lung cancer detection methods. This paper also highlights recent achievements, relevant research challenges, and future research directions. The rest of the paper is structured as follows [15]. describes the currently available medical lung imaging techniques for lung cancer detection; reviews some recently developed deep learning-based imaging techniques; presents lung cancer prediction using deep learning techniques; describes the current challenges and future research directions of deep learning-based lung imaging methods; and concludes this study.

ARCHITECTURE:

CAD-based lung cancer detection system. The figure is reused from reference ; no special permission is required to reuse all or part of articles published by MDPI, including figures and tables. For articles published under an open-access Creative Common CC BY license.

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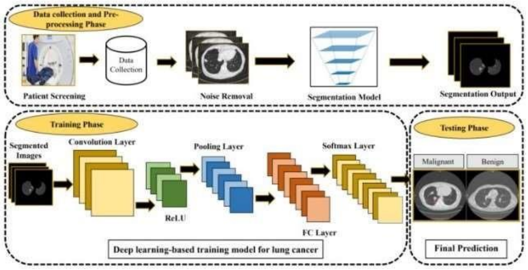

PROCESSING AND EVALUATION:

Pre-Processing Techniques : The pre-processed images are injected into a deep learning algorithm with specific architecture and training and tested on the image datasets. The image noise affects the precision of the final classifier. Several noise reduction approaches, such as median filter, Wiener filter, and non-local means filter, have been developed for pre-processing to improve accuracy and generalization performance. After denoising, a normalization method, suchas min-max normalization, is required to rescale the images and reduce the complexity of image datasets.

Performance Metrics

Several performance metrics have been used to evaluate the performance of deep learning algorithms, including accuracy, precision, sensitivity, specificity, F1_score, error, mean squared error (MSE), receiver operation characteristic (ROC) curve, over-segmentation rate (OR), under-segmentation rate (UR), Dice similarity coefficient (DSC), Jaccard Score (JS), average symmetric surface distance (ASD), modified Hausdorff distance (MHD), and intersection over union (IoU).

Accuracy assesses the capability concerning the results with the existing information features. Sensitivity is helpful for evaluation when FN is high. Precision is an effective measurement index when FP is high. The F1_score is applied when the class distribution is uneven. ROC can tune detection sensitivity. The area under the receiver operating characteristic curve (AUC) has been used to evaluate the proposed deep learning model. Larger values of accuracy, precision, sensitivity, specificity, AUC, DSC, and JS, and smaller values of Error, UR, OR, and MHD indicate better performance of a deep learning-based algorithm.

Accuracy=TP+TNTP+TN+FP+FN

Sensitivity=TPTP+FN

Specificity=TNTN+FP

Precision=TPTP+FP

F1_score=2TP2TP+FP+FN

Error=FP+FNTP+TN+FP+FN

CONCLUSION:

One of the most fatal diseases to have existed is lung cancer. This disease unfortunately is extremely tough to treat after having spread upto an extent or reaching a serious stage. Computer-Aided Detection (CAD) is one of the constantly growing technologies that help detect cancer by feeding in certain inputs containing patient-related information such as scans like CT-Scan, X-Ray, MRI Scan, unusual symptoms in patients or biomarkers, etc.

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LIDC-IDRI. By the means of this review paper, we aim to list out all the major researches that have been done over thepast years and can be improved upon to achieve better results.

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