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An Enhanced Automatic Lung Disease Diagnosis Scheme Using ECG Signals with Integrated Feature Extraction and Improved Deep Learning

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Abstract

An early detection of lung disease can avoid patient death by giving useful treatment. The human with related lung conditions nearly contains related electrocardiogram (ECG) signals. The ECG examination can be an analytical system employed on the screen for various lung diseases. Arrhythmias are discovered through patterns of ECG signals. Nowadays, most of the ECG analysis is done according to the medical team"s personal opinion, which may have led to more burden. Therefore, in this paper, an automatic lung disease diagnosis scheme is presented through an accurate ECG signal categorization using improved deep learning processes. Initially, ECG signal data is pre-processed with noise removal and QRS complex discovery schemes. Subsequently, an integrated feature extraction method is proposed in this paper to extract the ECG wave features. The presented automatic lung disease detection scheme is examined using the ECG signals dataset collected from a MIT-BIH arrhythmia database.

Keywords: *Lung disease detection, ECG signals, QRS complex discovery, integrated feature extraction, enhanced ECG signal categorization.*

1. 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. Many ECG systems have been extensively studied for lung cancer detection and classification. Compared to trained radiologists, ECG systems provide better lung nodules and cancer detection performance in medical images. Generally, the ECG-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 ECG system, which relies on image processing to capture reliable features. However, benign and malignant nodule classification is a challenge. Many investigators have applied deep learning techniques to help radiologists make more accurate diagnoses. The deep learning-based lung imaging techniques research mainly includes pulmonary nodule detection, segmentation, and classification of benign and malignant pulmonary nodules. Researchers mainly focus on developing new network structures and loss functions to improve the performance of deep learning models. Several research groups have recently published review papers on deep learning techniques. However, deep learning techniques have developed rapidly, and many new methods and applications have emerged every year. This research has appeared with content that previous studies cannot cover. [1]

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2. Method

2.1. Lung Cancer Prediction Using Deep Learning

This section presents recent achievements in lung cancer and nodule prediction using deep learning techniques. The processing includes image pre-processing, lung nodule segmentation, detection, and classification. (Figure 1)

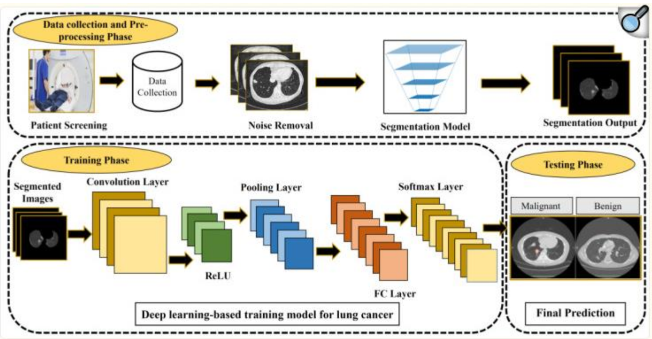

Figure 1 ECG-Based Lung Cancer Detection System

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2.2. Imaging Pre-Processing Techniques and Evaluation

2.2.1. 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, such as min-max normalization, is required to rescale the images and reduce the complexity of image datasets. [3]

2.2.2. 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. (Figure 2)

2.3. MIT-BIH Arrhythmia Datasets

Dataset	Sample Number
Lung image database consortium (LIDC)	399 CT images
Lung image database consortium and image database resource initiative (LIDC-IDRI)	1018 CT images from 1010 patients
Lung nodule analysis challenge 2016 (LUNA16)	888 CT images from LIDC-IDRI dataset
Early lung cancer action program (ELCAP)	50 LDCT lung images & 379 unduplicated lung nodule CT images
Lung Nodule Database (LNDb)	294 CT images from Centro Hospitalar e Universitario de São Joãao
Indian Lung CT Image Database (ILCID)	CT images from 400 patients

Figure 2 Dataset & Sample Number

3. Results and Discussion

3.1. Results

Compared to reinforcement and supervised learning techniques, unsupervised deep learning techniques (such as CNN, Faster R-CNN, Mask R-CNN, and U-Net) are more popular methods that have been used to develop convolutional networks for lung cancer

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detection and false-positive reduction. Previous studies have shown that CT is the most widely used imaging tool in the ECG system for lung cancer diagnosis. Compared to 2D CNN, 3D CNN architectures provide more promising usefulness in obtaining representative features of malignant nodules. To this day, only a few works on 3D CNN for lung cancer diagnosis have been reported. Deep learning techniques have achieved good performance in segmentation and classification. However, deep learning techniques still have many unsolved problems in lung cancer detection. First, clinicians have not fully acknowledged deep learning techniques for everyday clinical exercise due to the lack of standardized medical image acquisition protocols. The unification of the acquisition protocols could minimize it. [4]

3.2.Discussion

Most deep learning techniques were developed by non-medical professionals with little or no oversight of radiologists, who, in practice, will use these resources when they become more widely available. As a result, some performance metrics, such as accuracy, AUC, and precision, which have little meaningful clinical application, continue to be used and are often the only summary outcomes reported by some studies. Instead, investigators should always strive to report more relevant clinical parameters, such as sensitivity and specificity, because they are independent of the prevalence of the disease and can be more easily translated into practice. [5]

Conclusion

This paper reviewed recent achievements in deep learning-based approaches for lung nodule segmentation, detection, and classification. CNN is one of the most widely used deep learning techniques for lung disease detection and classification, and CT image datasets are the most frequently used imaging datasets for training networks. The article review was based on recent publications (published in 2014 and later). Experimental and clinical trial results demonstrate that deep learning techniques can be superior to trained radiologists. Deep learning is expected to effectively improve lung nodule segmentation, detection, and classification. With this powerful tool, radiologists can interpret images more accurately. Deep learning algorithm has shown great potential in a series of tasks in the radiology department and has solved many medical problems. However, it still faces many difficulties, including large-scale clinical verification, patient privacy protection, and legal accountability.

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