UNet Model for Segmentation of COPD Lung Lesions on Computed Tomography Images

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Abstract

The purpose of the research described in the article is to use machine learning algorithms to automatically detect symptoms of chronic obstructive pulmonary disease. Machine learning methods and neural network were used in chronic obstructive pulmonary disease. The issues addressed in this work are: Prevention of symptoms of chronic obstructive pulmonary diseases, achieving quick and accurate results through machine learning and neural networks, Use of effective machine learning techniques to obtain computed tomography images. In order to identify structural data for lung function testing and their important role in the diagnosis and treatment of COPD, machine learning classifiers were tested and tested. The accuracy of the data studied using the U-Net architecture to easily and quickly identify the symptoms of the disease with the classifier of machine learning using tomographic images has been proven to be effective.

Keywords

segmentation, neural network, COPD, computed tomography images

1. Introduction

As more studies are committed to the findings supported by the spread, it can be argued that after the pandemic of the new corona illness, scientists are concentrating on lung ailments more and more [1]. Almost always when there is pulmonary morbidity. Malignant lymph nodes in the lungs frequently progress into lung cancer, a major threat to human health that can even be fatal. A tiny percentage of pulmonary nodules in the lung or false properties may occasionally go undetected by doctors while they are doing an observation. As a result, when artificial intelligence is developed, intelligent algorithms are employed to support and direct the doctor's attention toward developing a precise diagnosis. For the purpose of capturing a portion of the lung parenchyma, the authors of the article [2] presented a multi-threshold approach. From the perspective of application, a model for segmenting the lung parenchyma was constructed in [3]. Few publications have, to date, described the constructed deep analysis simulation network for lung parenchyma segmentation [4]. It is simple and common procedure to segment the parenchyma using morphological models [5]. U-Net was used to optimize the extraction of lung parenchyma in [6]. The authors of [7] created a CNN network to segment the lung parenchyma. Unsupervised modeling clustering is used to recognize legal nodes and groups [8], to segment legal nodes in the active contour model that has been presented, and to construct fuzzy clustering in [9,10]. The authors of [11] employed a well-researched graph based on a preliminary cut to extract pulmonary nodes, [12] created an R-CNN mask, and [13] presents an artificial interactive method for extracting lung nodules. An adaptive morphological progressive neural network with two directions was

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constructed for the segmentation of pulmonary nodes in the publication [14]. Computer diagnostic techniques have been shown to be a helpful tool for doctors to use when making an accurate diagnosis. However, it is still challenging to examine weak pulmonary nodes and the complicated and varied characteristics of pulmonary nodes [15]. This contains the following specifically: (1) The computer-generated model does not correspond to the method of diagnosis used by doctors. (2) In the event that the lungs have nodules.

Being able to easily and quickly identify symptoms of chronic obstructive pulmonary diseases based on computer tomography images. Chronic obstructive pulmonary disease (COPD), diagnosed based on smoking, consumption of other harmful substances, presence of respiratory symptoms, and chronic airflow limitation confirmed by spirometry after bronchodilator. It is one of the leading diseases of morbidity and mortality worldwide. It is characterized by airway obstruction, shortness of breath, and decreased exercise tolerance.

In primary health care, the initial stage in the clinical diagnosis of COPD is the assessment of respiratory complaints: cough, sputum production, and dyspnea. Given the irreversibility of airflow limitation in COPD, these symptoms will have a chronic course, that is, exist for more than 12 weeks for 1 year or more [16]. The importance of studying the prevalence of respiratory symptoms is emphasized in a number of international studies, which show that in the adult population they can occur in 41–48% of cases [17, 18]. It should be taken into account that most of these studies were aimed at studying the prevalence of respiratory symptoms among smokers, people working or living in conditions of dust pollution, and the elderly [19-20]. However, as our studies have shown, in real practice among patients seeking medical care from family doctors, a high prevalence of chronic respiratory complaints was revealed, amounting to 58.9% [19]. However, the detection of symptoms alone is not enough to diagnose COPD due to their low prognostic value [22]. Decision this problem can be facilitated by the use of international standardized questionnaires, which are recommended for use in primary health care [23, 24]. Developing a diagnostic tool based on questionnaires can help in identifying a group of patients with a high risk of developing COPD, which is an urgent task for outpatient practice.

Sudden spontaneous weight loss and low body mass index put COPD patients at increased risk of death. Early and accurate detection of differences in body composition, appropriate treatment, such as improved nutrition and lung rehabilitation, should be carried out in time. According to the results of the EPISCAN II study in Spain, its prevalence among the population over 40 years old is 11.8% (14.6% in men and 9.4% in women) [25].

Symptoms of COPD can be diagnosed in several ways. Computed tomography imaging is currently the standard measure of body composition, however, computed tomography imaging is relatively expensive, may be available only in limited settings, is time-consuming, and involves exposure to ionizing radiation. [26] Given the ease of obtaining measurements from computed tomography images, body composition studies in COPD patients are performed using these images.

X-ray examination of patients with COPD can be conditionally divided into two stages. The first of which is aimed at the primary assessment of organs of the thoracic cavity and usually involves the use of conventional x-ray examination - X-ray or fluorography. Any of these studies are almost all patients with COPD at the stage of primary diagnosis or during an exacerbation of the disease. The second stage is an in-depth study of the morphology and function of the lung tissue and is aimed primarily at identifying emphysema and bronchiectasis, determination of the type and prevalence of pathological changes. The main technology in these cases is x-ray computed tomography (CT). Other imaging modalities, such as ultrasound and radionuclide imaging, magnetic resonance imaging are of limited value in the evaluation of COPD.

Neural networks [27] show recognition accuracy better than or comparable to humans in many recognition tasks, including road sign recognition, face recognition, and number recognition. Modern materials research worldwide, using X-ray microtomography and 3D image analysis, has always limited the accuracy of dense fibrous materials. However, it can be said that recent machine learning methods and especially deep learning are helping to overcome this challenge [28].

To obtain morphometric measurements of fiber bundles and to accurately estimate their density, it is necessary to achieve a first segmentation of sufficient quality. Among other applications, the proposed method thus allows the design of more realistic models of MDF material. Pneography is recommended as an outpatient method of monitoring respiratory diseases. However, its ambulatory nature makes recordings more susceptible to noise sources. Identifying and removing such noisy segments is critical because they can greatly impact the performance of data-driven decision support tools. In general, machine learning algorithms are used to separate noisy bioimpedance signals from clean ones in chronic obstructive pulmonary disease symptoms. There are different approaches to machine learning. Compare: heuristic algorithm, feature-based classification model (SVM) and convolutional neural network (CNN).

The utilization of various datasets to assess newly suggested models is a significant difficulty in the field of lung/lesion segmentation (and image segmentation in general). Additionally, there are no reference base models that may be used as a standard by which to compare the effectiveness of the suggested models. The description includes benchmarks for counting the number of lung issues visible on CT scans, such as the volume in [29] tests samples of 20 models of the number of lung segmentation in patients using COVID-19. In [30] compares raw trial algorithms developed by several research teams and offers additional comparison studies on issues like lung nodule segmentation. You should take note that research on image segmentation issues uses a deep learning approach and has successfully been applied to non-medical images like coral reef images [31], where the authors test four models, and to images of cities with altitude [32], where the authors test 12 different models.

Taking as an example a data set of 47 patients with chronic obstructive pulmonary disease with limited breathing, their breathing was recorded during the experiment using a bioimpedance device and a spirometer. It can be observed that the accuracy of both machine learning approaches (SVM: 87.77 ± 2.64% and CNN: 87.20 ± 2.78%) is significantly higher compared to the heuristic approach (84.69 ± 2.32%). Moreover, no significant differences were observed between the two machine learning approaches [33, 34].

A corresponding value of 92.51 ± 1.74% was obtained using the neural network model. These results suggest that a data-driven approach may be useful for the task of detecting artifacts in respiratory chest bio-impedance signals.

2. Results of using machine learning algorithms to identify COPD symptoms

U-net was originally invented and first used for biomedical image segmentation. Its architecture can be broadly considered as an encoder network connected to a decoder network. Unlike classification, where the end result of a deep network is the only thing that matters, semantic segmentation requires not only discrimination at the pixel level, but also a mechanism for projecting the discriminative features learned at different stages of the encoder into pixel space.

The encoder is the first half of the architecture diagram. This is usually a pre-trained classification network such as VGG/ResNet, which uses convolutional blocks and then uses a maxpool-reduced model to encode the input image into feature representations at several different levels.

The decoder is the other half of the architecture. The goal is to semantically project the discriminative features learned by the encoder (low resolution) into pixel space (high resolution) to obtain dense classification. The decoder consists of sampling and combining, followed by constant convolution operations.

U-Net is an architecture for semantic segmentation. It consists of a short path and a wide path. A contract string follows the typical architecture of a convolutional network. It consists of repeated application of two 3x3 convolutions (unfilled convolutions), each with a corrected linear unit (ReLU), and a 2x2 max pooling operation with two steps to obtain the subsample. At each downsampling step, we double the number of feature channels. Each step in the expanded path consists of sampling a feature map, followed by a 2x2 convolution ("roll up") that halves the number of feature channels, concatenation with the corresponding clipped feature map from the contract path, and two 3x3 convolutions, each followed by ReLU. At each convolution, clipping is required due to the loss of border pixels. In the last layer, a 1x1 conversion is used to map each 64-component feature vector to the required number of classes. In total, there are 23 convolutional layers in the network.

First announced in 2015, the U-Net architecture revolutionized deep learning. Architecture won the Cell Tracking Challenge at the 2015 International Symposium on Biomedical Imaging (ISBI) by a wide margin in multiple categories. Some of their work includes segmentation of neuronal structures in electron microscopy stacks and transmitted light microscopy images.

With this U-Net architecture, segmentation of 512X512 images can be computed using modern GPUs in less time. Due to the great success of this architecture, there have been many versions and modifications. Some of them focus on LadderNet, U-Net, Recurrent and Residual Convolutional U-Net (R2-UNet) and U-Net with residual blocks or blocks with dense connections.

Although U-Net is an important breakthrough in the field of deep learning, it is equally important to understand the previous methods used to solve similar tasks. One of the main examples to be completed was the sliding window method, which won the EM segmentation challenge at ISBI in 2012 by a large margin. The sliding window method was able to generate a wide range of sample patches apart from the original training data set.

This is because the result obtained in Figure 1 uses the meshing method of the sliding window architecture by creating the class label of each pixel as separate units by providing a local area (patch) around that pixel. Another achievement of this architecture was that it can be easily localized on any training data set for relevant tasks.

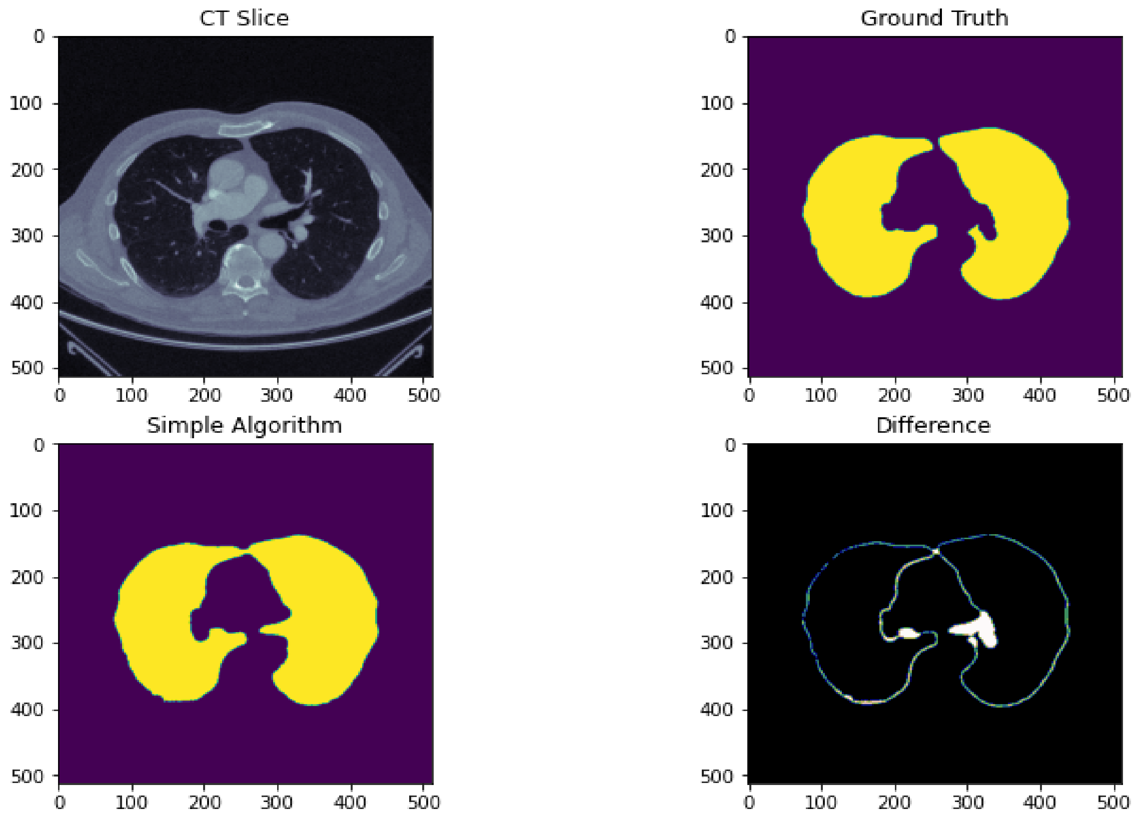

Figure 1: Data visualization using U-Net

However, the sliding-window approach suffers from two major drawbacks that confront the U-Net architecture. Since each pixel is treated individually, the resulting patches we overlap a lot. Thus, the total surplus was generated more. Another limitation is that the overall training procedure was very slow and required a lot of time and resources. The viability of the network is questionable for the following reasons.

U-Net is an elegant architecture that solves most of the problems that arise. It uses the concept of fully convolutional networks for this approach. The goal of U-Net is to capture both context features and localization. This process has been successfully completed for the type of architecture that was built. The main idea of the implementation is to use sequential conformal layers performed with immediate upsampling operators to achieve high-resolution results on the input images.

Data visualization (Figure 2). Now that we have collected and preprocessed our data, our next step is to briefly review the dataset. A dataset needs to be analyzed by displaying both the image and its corresponding segmented output. This segmented output with masking is often referred to as the ground truth annotation. Along with the pillow library, I-Python uses the display option to randomly display the selected image.

	precision	recall	f1-score	support
False	0.99	0.99	0.99	204802
True	0.96	0.96	0.96	57342
accuracy			0.98	262144
macro avg	0.98	0.97	0.97	262144
weighted avg	0.98	0.98	0.98	262144

Figure 2: Accuracy detection with U-Net architecture

The most effective, qualitative method was selected using various methods of determining accuracy:
Gaussian Naive Bayes: 0, 79
K-NN classifier: 0.94
Decision Tree Classifier: 0.912
U-Net: 0.98
Data trained using the U-Net architecture showed high accuracy.

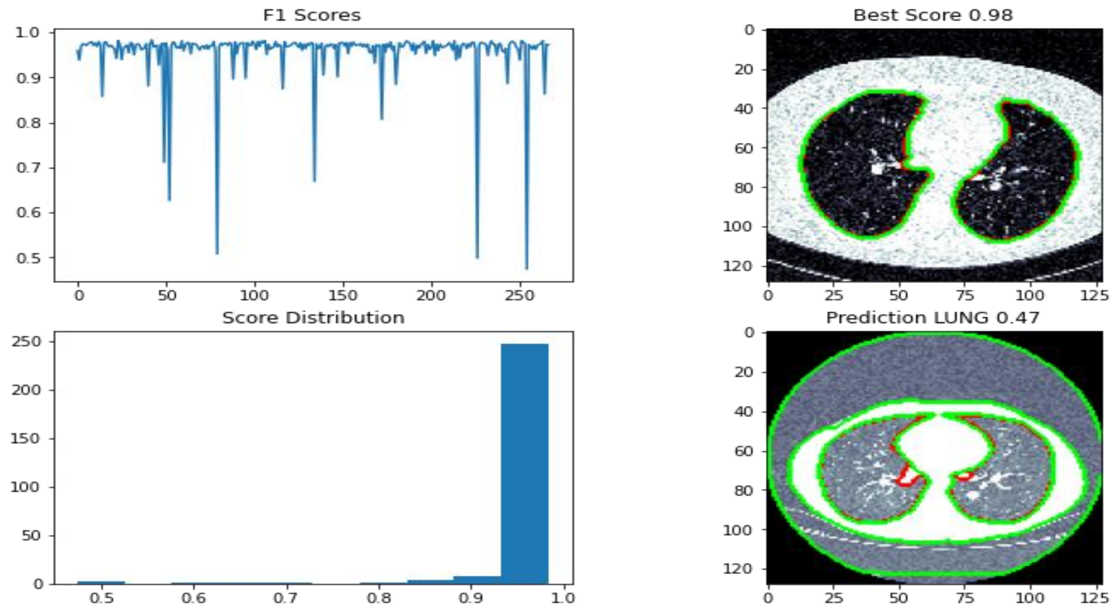

Figure 3: Accuracy of trained data using U-Net architecture

Figure 4 shows the image of identifying symptoms of chronic obstructive pulmonary disease using the U-Net architecture.

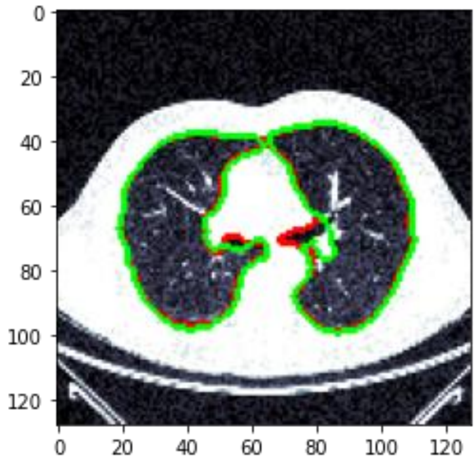

Figure 4: Chronic obstructive pulmonary disease symptom detection using U-Net architecture

As shown below, green areas and red areas indicate the presence of symptoms of chronic obstructive pulmonary disease. Green areas indicate the initial stages of disease symptoms, that is, the onset, and red areas indicate the direct presence of disease viruses.

3. Conclusion

A U-Net model of segmentation for lung function assessment was designed to aid in the clinical application of machine learning classifiers, taking into account structural data for pulmonary function testing and their significant importance in the diagnosis and management of COPD. The best approaches to identify the symptoms of the condition were taken into consideration, compiled, and results were achieved using machine learning classifiers. Chronic obstructive pulmonary disorders. It has been demonstrated that data trained using the U-Net architecture is more accurate than data trained using other techniques.

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