Lung Function Decline Predicting Using Improved EfficientNet

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Abstract-Pulmonary fibrosis (pf) is a common outcome of various lung diseases, with scarring of lung tissue as the main manifestation, and if the scope of involvement is extensive, it leads to a reduction in lung volume, a significant decrease in lung function, and a serious impact on the quality of life of patients. Using CT scanning to examine high-risk people is an effective means to find early lung cancer. With the development of technology, computer-aided diagnosis plays a very important role in the cancer diagnosis. We state the related work and proposed an improved EfficientNet. We choose Laplace Log Likelihood as our experiment metrics. The higher Laplace Log Likelihood is, the better performance the model will gain. We can see the result that our improved EfficienNet model owns the best performance with -6.89 Laplace Log Likelihood, which is 0.23, 0.22, 0.15 and higher than Resnet34, Resnet50 and EfficientNet respectively.

Keywords: Pulmonary fibrosis, lung diseases, CT scans, EfficientNet, Laplace Log Likelihood

I. Introduction

Lung cancer has become one of the highest cancer incidence rate and death rate, and millions of people worldwide die from lung cancer every year, according to research. Since the 21st century, with the growth of the number of smokers and the increasingly serious environmental pollution, the number of patients with lung cancer has also increased year by year. The survival rate of patients with lung cancer can be significantly improved if they can be diagnosed and treated as soon as possible. For example, the five-year relative survival rate of patients with early lung cancer can reach 50%, while that of patients with late lung cancer is less than 5%. And because the symptoms of early patients are not obvious and difficult to detect, the final treatment has developed into advanced lung cancer, thus missing the best treatment time. Therefore, effective early screening and diagnosis of lung cancer is very important in cancer prevention and treatment.

Pulmonary fibrosis (pf) is a common outcome of various lung diseases, with scarring of lung tissue as the main manifestation, and if the scope of involvement is extensive, it leads to a reduction in lung volume, a significant decrease in lung function, and a serious impact on the quality of life of patients. In particular, idiopathic pulmonary fibrosis (ipf) is the most typical representative, and its pathology and/or imaging are chronic progressive lung diseases of common interstitial pneumonia. The cause of IPF is unknown, the prognosis is extremely poor, and the average survival after diagnosis is only 3-5 years.

Using CT scanning to examine high-risk people is an effective means to find early lung cancer. The number of such people is huge, and the workload of imaging doctors increases sharply. Therefore, computer-aided diagnosis plays a very important role. At present, a lot of research work has been done based on the traditional statistical machine learning methods, and some results have been achieved. In our paper, we state the related work in section II. And section III shows our model for this task: improved EfficientNet while section IV introduces the experiment results and compared experiments. In the last section V, we concluded our whole work and proposed the further adjustment in the future.

II. Related Work

The traditional processing idea of medical image analysis method is to preprocess the data, artificially design the feature extractor according to the characteristics of the image, and analyze the medical image in combination with various classification algorithms in machine learning, such as support vector machine algorithm and K-means clustering algorithm, so as to realize the automatic diagnosis of various diseases.

[1] It is the first time to use deep learning method to detect mitosis in pathological images, which has achieved great success. After that, deep learning and convolution neural network technology has been extensively applied in the field of medical imaging analysis, such as breast cancer pathological image classification [2], lung cancer pathological image classification [3], cell morphology processing [4], gland pathological [5] segmentation. At present, the research in the field of lung disease analysis mainly includes two aspects. Research on segmentation and classification based on imaging image and pathological image. Imaging images include chest X-ray, high resolution CT (HRCT) and isotopic lung scanning; Pathological images mainly refer to whole slide image (WSI) images of histopathology. [6] Train an independent CNN model for three binary classification tasks, focusing on predicting 1-year, 3-year and 5-year renal survival. [7] A convolution neural network with 11 continuous convolution linear correction units and batch normalization (BN) is proposed. The network is used for pathological image segmentation and can effectively distinguish fibrosis region, muscle cells and background. [8] Et al. Proposed an automatic classification model of lung tissue based on resnet18 and resnet3454), which can distinguish healthy tissue regions and pathological tissue regions of cystic fibrosis lung disease (cfld) through CT scanning images, so as to evaluate and judge the degree of cfld lesions. [9] A convolution neural network is proposed to classify cystic fibrosis tissues in CT scanning images, which can distinguish healthy lung tissues, bronchus and inflammatory sites. [10] The exclusion model and classification model are established. The exclusion model is

composed of four categories: two exclusion categories - background and vascular boundary, and two include category - normal tissue and fibrous area. When the classification model is applied to the exclusion model, the background, perivascular collagen, collagen of alveolar wall and normal tissue can be distinguished. [11] Two, two and a half and three-dimensional convolutional neural network models are combined to identify and classify interstitial lung disease (ILD) in CT images. [12] Combining VGG, data enhancement and spatial transformation network (STN) with CNN, a new hybrid deep learning framework (vdsnet) is proposed to simplify doctors' detection of chronic obstructive pulmonary disease, pneumonia, asthma, tuberculosis and pulmonary fibrosis.

- Our Contribution
- ✓ We improve the EfficientNet to create our predicted model
- ✓ We introduce our dataset and do some analysis.
- ✓ In the experiments process, we do the comparing experiments and the result shows that our model performed better than the other models.

III. METHODOLOGY

Efficientnet [13] is a network model proposed by Mingxing Tan and Quoc v. le in 2019. They proposed a new network scaling method, which structurally adjusts the convolution neural network through a composite coefficient, and uniformly scales the width,

depth and resolution of the input image to change the network dimension. Different from traditional methods, the expansion of convolutional neural network is more efficient. Extended network depth is now widely used in the training of neural networks. Deep networks can extract features with higher complexity and semantic level to help the learning of target data sets.

However, deep networks are prone to the problem of gradient disappearance. Increasing network width is also widely used. The width of the network is the number of channels of the characteristic graph. Increasing the network width can make the feature map have more channels, and more image features can be obtained by convolution on each channel, which can make the model have better expression ability. A wide network can usually learn a variety of features, which can easily train the network. However, it is precisely because the width of the network is enough that the depth is not enough. Although the extracted features are rich, the degree of semantics is not high. If the resolution of the network input image is improved, by enriching the receptive field of the network, the network can learn as much detail information in the image as possible, and the performance of the network can also be improved. However, the large-scale network expands in any aspect, and its accuracy is low.

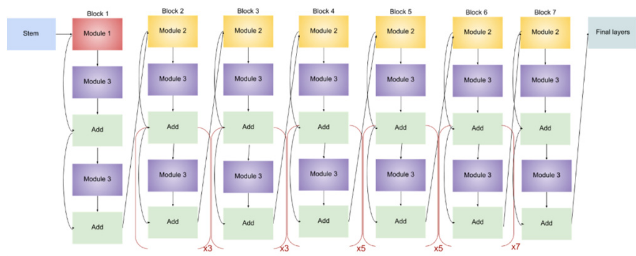

Figure 1: EfficientNet-b5 model

In our model, we proposed the improved EfficientNet. The whole structure of improved EfficientNet is shown in the following figure 2.

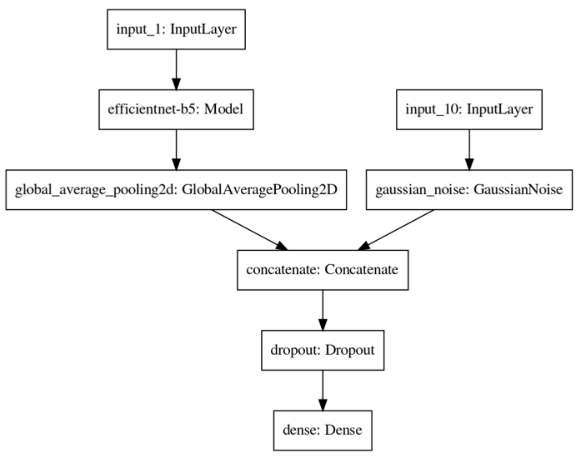

Figure 2: our model's Architecture

IV. EXPERIMENTS

A. Experiments data

Our dataset is provided by Kaggle platform. In the dataset, you are provided with a baseline chest CT scan and associated clinical information for a set of patients. A patient has an image acquired at time Week = 0 and has numerous follow up visits over the course of approximately 1-2 years, at which time their FVC is measured.

- ✓ In the training set, an anonymized, baseline CT scan and the entire history of FVC measurements are provided. The CT scan is shown in figure 3.

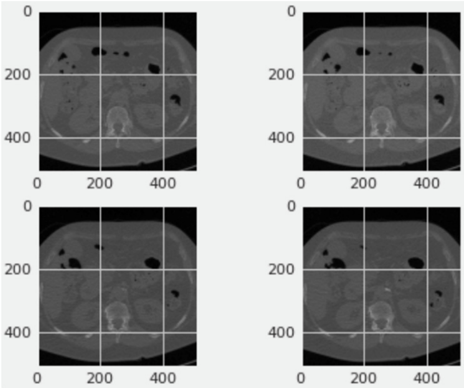

Figure 3: input CT scan

- ✓ In the test set, a baseline CT scan and only the initial FVC measurement are provided. We need to predict the final three FVC measurements for each patient, as well as a confidence value in your prediction.

The divided columns in the training and text dataset are:

- ✓ Patient- a unique Id for each patient (also the name of the patient's DICOM folder)
- ✓ Weeks- the relative number of weeks pre/post the baseline CT (may be negative)
- ✓ FVC - the recorded lung capacity in ml
- ✓ Percent- a computed field which approximates the patient's FVC as a percent of the typical FVC for a person of similar characteristics
- ✓ Age
- ✓ Sex
- ✓ Smoking Status

The sex distribution is shown in figure 4. We can see that male is tended to get ill.

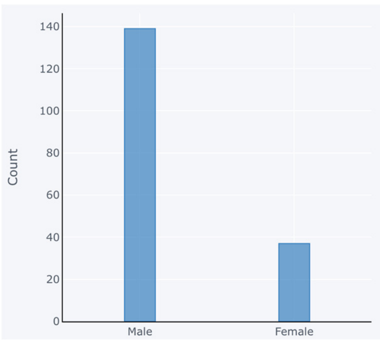

Figure 4: sex distribution

B. *Experiments metrics*

We use a modified version of the Laplace Log Likelihood to evaluate our model's result. In medical applications, it is useful to evaluate a model's confidence in its decisions. Accordingly, the metric is designed to reflect both the accuracy and certainty of each prediction.

For each true FVC measurement, we will predict both an FVC and a confidence measure (standard deviation σ). The metric is computed as:

$$\begin{aligned} \sigma_{\text{clipped}} &= max(\sigma, 70), \\ \Delta &= min\left(\left|FVC_{\text{true}} - FVC_{\text{predicted}}\right|, 1000\right), \\ \text{metric} &= -\frac{\sqrt{2}\Delta}{\sigma_{\text{clipped}}} - \ln\left(\sqrt{2}\sigma_{\text{clipped}}\right). \end{aligned} \tag{1}$$

The error is thresholded at 1000 ml to avoid large errors adversely penalizing results, while the confidence values are clipped at 70 ml to reflect the approximate measurement uncertainty in FVC. The final score is calculated by averaging the metric across all test set Patient Weeks (three per patient).

C. *Experiment setting*

Table 1 shows that what hyper parameters we choose in our training process.

Table 1: experiment setting

Learning rate	1e-4
Optimizer	adam
Batch size	32
Epoch	35

D. *Compared experiment and result*

The experimental results of competing models and our model are shown in table 2.

Table 2: experiment results

Models	Laplace Log Likelihood
Resnet34	-7.12
Resnet50	-7.11
EfficientNet	-7.04
Proposed Model	-6.89

We do the compared experiment using the same metrics and same dataset. The higher Laplace Log Likelihood is, the better performance the model will gain. We can see the result that our improved EfficienNet model owns the best performance with -6.89 Laplace Log Likelihood, which is 0.23, 0.22, 0.15 and higher than Resnet34, Resnet50 and EfficientNet respectively.

V. Conclusion

Effective early screening and diagnosis of lung cancer is very important in cancer prevention and treatment. With the development of technology, Computer-aided diagnosis plays a very important role in the diagnosis. A lot of research work has been done based on the traditional statistical machine learning methods, and some results have been achieved. In our paper, we state the related work in section II. And section III shows our model for this task: improved EfficientNet while section IV introduces the experiment results and compared experiments. In the last section V, we concluded our whole work and proposed the further adjustment in the future. We choose Laplace Log Likelihood as our metrics. The higher Laplace Log Likelihood is, the better performance the model will gain. We can see the result that our improved EfficienNet model owns the best performance with -6.89 Laplace Log Likelihood, which is 0.23, 0.22, 0.15 and higher than Resnet34, Resnet50 and EfficientNet respectively.

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