Machine Learning-Based Classification of Lung Diseases

An Approach

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Abstract

The radiological evaluation of lung tissue is pivotal for an accurate diagnosis of lung diseases. Current advances in machine learning technologies have forwarded the automatic detection of pathological structures in human tissue based on radiographs. Current advances in machine learning technologies have the potential to increase the diagnosis precision and may help to reduce human errors. In this paper we present a novel approach for the use of machine learning to improve the general decision process that relies on the judge-advisor theory and machine learning in a medical context. Our goal is to help doctors diagnose conditions so that they have more time for patients and their treatment. Our approach uses an artificial neuronal network to analyze the lung radiographs. Recent research has shown that this machine learning method is the state-of-the-art algorithm for image classification. We test our approach empirically.

Motivation, Goals and Research Question

- Motivation:
  - CNNs have great potential [2]
  - Mechanical automation can reduce the error rate [1]
- Goals and Research Questions:
  - It is possible to develop a machine learning approach to detect lung diseases?

Previous Research

Convolutional neural networks (CNNs), which are assembled of multiple process layers to learn the representations of data with multiple abstract levels, are the most successful machine learning models in recent years [5]. CNNs are extensively used in image classification, obtaining encouraging classification accuracy over large-scale datasets compared to hand-engineered features based methods [6].

Data acquisition and Methods

We use the classical machine learning approach to train a CNN Network. In line with our research question we train the CNN for image classification.

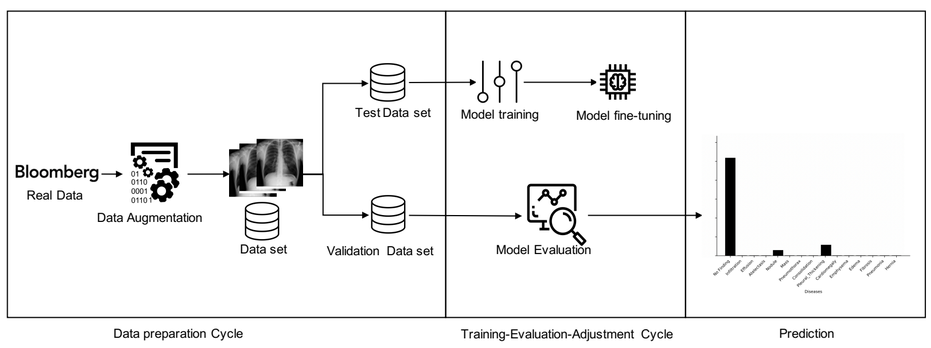
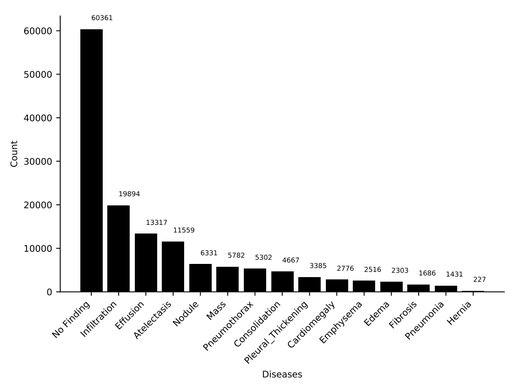


Figure 1: Our approach

For this study, we use a huge dataset of more than 119.000 lung images from patients that suffer from one out of 15 different widespread lung diseases and which can be used to train the artificial neuronal network. We have collected a new chest X-ray database, namely ChestX-ray8, which comprises 112,100 frontal- view X-ray images of 32,717 unique patients with the text-mined eight disease image labels (where each image can have multi-labels) for the National Institutes of Health (NIH) in the United States of America. We use an open-access dataset repository from the NIH clinical center - Americans research hospital[1]. For the sample selection we have decided to use the eight most common lung diseases [8]. The figure shows the distribution of the lung diseases in our data set.



[1] https://nihcc.app.box.com/v/ChestXray-NIHCC

Figure 2: Raw data set of X-Ray images.

In the context of model selection and specification we use the Inception V3 architecture. In our setting we use initial weights from the ImageNet dataset; therefore we follow the state-of-the-art concept of transfer-learning for ANN in line with works of [2] of [4]. In the context of fine tuning, we use as starting point the parameters of familiar literature. Therefore all layers use the same global learning rate of 0.001 and a decay factor of 16 [7]. Additionally, we use the RMSProb with a decay of 0.9, momentum of 0.9 and elision of 0.10 [2]. We decided to use 3000 epochs to learn this model in consequence of the result of the current research [3]

Results

Our current results indicates a set of problems. The figure shows an example of the primary problem. The network memorizes the images in the test set.

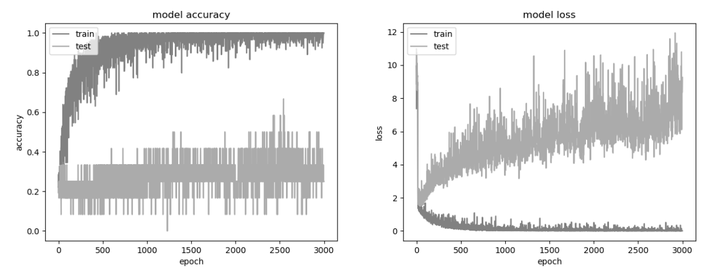


Figure 3: Results with Inception V3.

However, the test images for the network are hardly recognizable. After systematic testing of different parameter combinations and modifications of pre-processing techniques, we get the same results.

Conclusions

- The evaluation of our results shows that the automated identification of lung diseases is a difficult task.
- In this context an additional issues is the unstable environment of tensorflow in combination with python and docker. System crashes and memory issues are not uncommon.
- In addition, we have started to perform an image filtering.
- First tests with other network architectures show the weaknesses of a relatively large network structure like the inception V3.

Forthcoming Research

With our results from previous research we decide to leave the inception V3 architecture and reprogramming our environment in Matlab based on the hand selected images, the AlexNEt architecture and a MATLAB implementation. The new studies in our new environment show promising results.

References

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