

Udacity Machine Learning Engineer Capstone Project

Proposal: Histopathologic Cancer Detection

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1 Domain Background

The field of digital pathology has facilitated image analysis algorithms to assist and automate diagnostic tasks [1]. A proven approach is to use Convolutional Neural Networks (CNNs), a type of deep learning model most commonly applied to analyze image. CNN has been shown to outperform pathologists in a variety of diagnostic tasks [1].

This project aims to identify metastatic cancer in small image patches taken from larger digital pathology scans [1]. Early detection and treatment of cancer play a crucial role in patient's survival rate. By the time symptoms appear, cancer may have begun to spread and be harder to treat. We use CNN to predict whether an image contains at least one pixel of tumor tissue [1], therefor help improve early diagnosis of cancer.

2 Problem Statement

Given images of digital pathology scans, determine whether there is at least one pixel of tumor tissue in the images. We approach the problem as a binary classification of a "tumor(1)" class and a "no tumor(0)" class.

3 Datasets and Inputs

The dataset is provided by Kaggle for a past competition [2]. It consists of a large number of small pathology images to classify. The link to the dataset can be found here.

The dataset contains of 220,025 training images; about 60% of them are from normal patients, and the remaining 40% contains tumor pixel. Each image is 3-channel color image with size of 96x96 pixels in tiff format. Our task is to classify and label the 57,459 images in the test set.

4 Solution Statement

We will solve this problem by using Convolutional Neural Network (CNN) that has proved to be successful in classifying image. The solution is a binary classification model capable of predicting whether an image contains tumor or not.

The CNN model that we use will be acquired via transfer learning of VGG-16. VGG-16 was introduced in the ImageNet Large Scale Visual Recognition Challenge in 2014. Currently, VGG-16 has been used to detect cancer through medical scans such as in [3], [4], and [5]. We will use the convolutional and pooling layers of the VGG-16, while adding our own linear layer(s) at the end for our classification problem.

In [3] and [4] retraining or fine-tuning of the VGG-16 layers are required, while in [5] it is not. Due to our computational constraint, we will not retrain our VGG-16 layers and only perform fine-tuning if necessary. We will focus on tuning the hyperparameter of our linear layer(s). Our dataset size is relatively large, therefore we might not need data augmentation.

5 Benchmark Model

A work in [1] found that rotation equivariance significantly improves tumor detection performance on a challenging lymph node metastases dataset. A similar method might be adapted in our solution.

We find a variety of projects on Github that solved this particular problem with different strategies, as displayed in Table 1. This benchmark acts a reference that will serve to assess how our final model perform.

Table 1: Past Projects on Github

| Author | Model | Accuracy |
|-----------|-------------------|----------|
| O. Boom | Resnet50 | 80.89% |
| G. Surma | Xception + NasNet | 95.8% |
| K. Garima | Xception | 93.74% |

6 Evaluation Metrics

Our model is optimized using only one metric, accuracy, and evaluated with it and two other metrics, precision and recall. The short explanations of each of metric, for our case, are:

- Accuracy: the number of correct classification divided by the total number of classification
- Precision: the number of correct tumor detection divided by the total number of tumor detection
- Recall: the number of correct tumor detection divided by the number of tumor images

7 Project Design

Our model is built using Python with Tensorflow, Keras, Numpy, and Panda libraries.

7.1 Workflow

The project's workflow is displayed by figure 1.

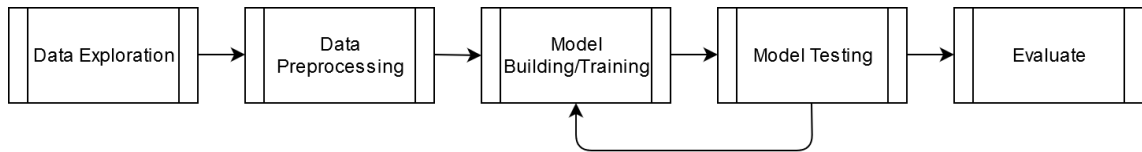


Figure 1: Project Workflow

First, we will explore the data and get an understanding of it. We handle outlier either by deleting it or transforming it. After that, we will perform basic cleaning and processing to the data if necessary. Next, we will build the CNN model using a pre-trained VGG-16. We will use the convolutional and pooling layers of the VGG-16, while adding our own linear layer(s) at the end for our classification problem. We then test our model and see whether it reaches our desired accuracy, and if not, we will tune our model's hyperparameter. This iteration of tuning and testing will continue until we get a desired accuracy. Finally, we will evaluate the performance of our network using evaluation metrics as explained in Section 6.

As mentioned in Section 4, we will not retrain our VGG-16 layers and only perform fine-tuning if necessary. We focus on tuning the hyperparameter of our linear layer(s), such as

learning rate, number of training epoch, optimizer type (Adam, RMSprop, Momentum, etc) and gradient descent type (Stochastic, Batch, Minibatch).

References

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- [3] Q. Guan, Y. Wang, B. Ping, D. Li, J. Du, Y. Qin, H. Lu, X. Wan, and J. Xiang, “Deep convolutional neural network vgg-16 model for differential diagnosing of papillary thyroid carcinomas in cytological images: a pilot study,” *Journal of Cancer*, vol. 10, no. 20, p. 4876, 2019.
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