Problem Description

Lung cancer has been a major worldwide public health problem. Lung cancers are malignant lung tumors characterized by an abnormal mass of lung tissues growing out of control. It is known for having the highest mortality rate among all tumors. According to the data from American Lung Association, the lung cancer five-year survival rate is only 18.6 percent, which is significantly lower than most other types of cancer. Nevertheless, the lung cancer five-year survival rate is 56 percent for cases detected in the early stage when the cancer cells are still contained within the lungs. Thus, the early detection and treatment of lung cancer are essential to increase the chance of survival.

In the early stage, lung cancer does not always lead to symptoms. Moreover, even when there are symptoms, these symptoms are easily confused with the symptoms of other diseases. Doctors would often not confirm a patient has lung cancer until they recognize a tumor on an imaging test, such as a Computed Tomography (CT) scan. Therefore, CT is considered the most effective and cheapest method of detecting lung cancer at an early stage. However, diagnostic imaging test results, such as CT scans, are challenging to decipher. Only radiologists are qualified to interpret radiographic exams and make judgments officially. So, radiologists are held to extremely high standards of training and practice. A typical radiologist would have spent 13 years on rigorous schooling and professional training before they are qualified to offer an official diagnosis. Since it requires lengthy qualifications to become a radiologist, researchers have made a great effort to develop imaging technology to detect and classify tumors in clinical images such as CT scans.

Related Works

There are various architectures made by researchers and scholars in a wide range of computer vision tasks, and one of the most popular models is VGG16, which is also used in this paper. VGG16 was introduced by Karen Simonyan and Andrew Zisserman from the University of Oxford. VGG15 is an improved model based on AlexNet. It replaces large kernel-sized filters, which are in the size of 11 or 5, with repeated 3×3 kernel-sized filters in succession. It is widely used in many research fields due to its ease of implementation. It performs specifically well when benchmarking on a particular task.

The other model we are going to use in this project is ResNet. ResNet, short for Residual Network, is a specific neural network introduced in 2015 by Kaiming He et al. Unlike the previous model with less than 20 layers, ResNet provides a way to create models that can have as many as 101 layers with skip connections, which means regularization would skip any layer hurting the performance of architecture.

Over the past few years, various curriculum learning algorithms have been proposed to enhance the accuracy of cancer image classification. In *On the Power of Curriculum Learning in Training Deep Networks*, Guy Hacohen and Daphna Weinshall design a curriculum that involves a non-uniform sampling of mini-batches to train networks. They decompose their curriculum learning into two tasks: (i) Define scoring functions to sort each sample in the data by its difficulty, and (ii) develop pacing functions to determine the pace by which data is presented to the network. The algorithms with curriculum learning display noticeable improvement (in terms of final accuracy) in image classification from vanilla algorithms. While their curriculum shows remarkable results, the dataset Guy and Daphna use are CIFAR-10 and CIFAR-100 instead of cancer images.

Proposed Work

Experts and scholars have explored various techniques and models for problems such as clinical detection, classification, and staging of tumors over the past few years. One hotspot among all research topics is using convolutional neural networks (CNN) to detect and classify lung cancer. CNN is widely used in many research fields due to its ease of implementation, and it has made significant progress in image processing, image recognition, and other areas. It performs specifically well when benchmarking on a particular task. There are various architectures made by researchers and scholars in a wide range of computer vision tasks. In this project, we plan to use two different CNN models: ResNet and VGG-16 to classify the normal images and tumor images. To improve our testing accuracy, we plan to apply curriculum learning to each model and find out to what extent it can help the model improve the classification accuracy.

Evaluation Metric

We will use final testing accuracy to evaluate our CNN models. The data we will use in this project is from The Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD) lung cancer dataset, collected over three months in the fall of 2019. The IQ-OTH/NCCD dataset contains CT scans of human chests with lung cancer in various stages and regular patients. All the CT scans are diagnosed by oncologists and radiologists from the two specialist hospitals, ensuring classification accuracy. The sample space includes 110 patients, grouped into three categories: normal, benign, and malignant. Forty of these cases are diagnosed as malignant; 15 cases are diagnosed as benign; 55 are classified as normal cases. Moreover, for each case, about 10 representing CT scan slices of the human chest with different sides and angles are selected from the CT image sequence, which provides 1097 CT scans in total.

The 110 cases vary in gender, age, educational attainment, area of residence, and living status to eliminate unwanted skewness as much as possible. Moreover, all identities were waived before utilizing this project. Our group also manually removed labels and timestamps to exclude confounding factors that may affect the performance of the analysis. To compare different models, we divide the dataset into a training (80%) set and a testing (20%) set. After training our models using the training data, we will use the trained models to classify testing data and determine the quality of models with testing accuracy.

Reference

Hacohen, Guy, and Daphna Weinshall. "On the Power of Curriculum Learning in Training Deep Networks." 29 May 2019.

American Lung Association. "Lung Cancer Basics." *Www.lung.org*, www.lung.org/lung-health-diseases/lung-disease-lookup/lung-cancer/basics.

American Lung Association. "Lung Cancer Fact Sheet | American Lung Association." Www.lung.org, 27 May 2020, www.lung.org/lung-health-diseases/lung-disease-lookup/lung-cancer/resource-library/lung-cancer-fact-sheet.

Alyasriy, Hamdalla. "The IQ-OTHNCCD Lung Cancer Dataset." *Data.mendeley.com*, vol. 1, 19 Oct. 2020, data.mendeley.com/datasets/bhmdr45bh2/1, Accessed 26 Jan. 2022.

Simonyan, Karen, and Andrew Zisserman. Very Deep Convolutional Networks for Large-Scale Image Recognition. 6, arXiv, 2014, doi:10.48550/ARXIV.1409.1556.

He, Kaiming, et al. "Deep residual learning for image recognition." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.