Computer Vision for Lung Cancer Detection

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Deep learning can aid in early detection and cancer-type classification through medical imaging, resulting in early treatment and lowering death rates of patients. One way to implement such technology is through Convolutional Neural Network models (CNN), as proven by previous research. For instance, by implementing a 3D CNN model that compiles lung CT scans, segments them into regions, and then uses an algorithm to classify the different types of tissues and cancers (benign or malignant) found. [Wang 2022] Likewise, this article aims to forge a deep-learning model that accurately identifies cancer in lung tissue scans. By feeding a pre-trained CNN model lung tissue images that contain a tumor, stroma, or neither, we looked for the specific patterns that define these conditions. After transforming the data and adjusting the model with techniques to avoid overfitting, we validated the model by testing if the given results matched the expected labels of our testing set. Consequently, the resulting model showed highly precise and accurate results, with a small loss. Therefore, using deep learning to aid healthcare practices can show to be as valuable as professionals in this sector, assisting in the early diagnosis and treatment of lung cancer patients.

CCS Concepts: • **Computing methodologies** → **Neural networks**.

Additional Key Words and Phrases: Machine Learning, Deep Learning, Convolutional Neural Networks, Lung cancer, Medical Imaging

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1 INTRODUCTION

Medical imaging has proven to be a highly useful tool in the sphere of healthcare, assisting in diagnosing and treating a patient's body. In cases where there are no external signs or symptoms, medical imaging is essential to avoid a delayed diagnosis. However, even medical professionals depend on a keen eye and rich experience to analyze medical images properly, thus the need for an efficient technological proposal has risen. As the medical and AI fields have continued to evolve, deep learning approaches have become widely used for early analysis. For context, deep learning is a branch of AI that aims to model data processing inspired by the human brain. The model learns through several processing layers that break down complex real-life concepts (image, audio, text, etc.) into a series of simple mappings. That way, the system can "learn" about the world from experience/data, resulting in a flexible and high-level type of machine learning. [Bengio et al. 2017] In particular, we will be discussing its role in lung cancer detection. Lung cancer is a noteworthy health concern. In Canada alone, according to the Canadian Cancer Society [Society 2023], it is one of the most commonly found cancers: every day, around 85 Canadians are diagnosed with lung cancer and 56 Canadians will die from it. Although it is normal to assume that lung cancer is merely caused by smoking, it can also develop from exposure to carcinogens present in the environment (air and water contaminants, food pollutants, daily products, and so on) or simply be passed down by genetics. In other words, everybody is at risk of this life-threatening disease, no matter how many preventative measures one might take. However, it is important to note that timely detection and intervention can better the chances of survival. Moreover, deep learning models have the ability to process large amounts of data in a relatively fast manner. As a result, they can help identify subtle signs and complex patterns that surpass human processing limits. This is best exemplified by the article "Deep Learning Techniques to Diagnose Lung Cancer," [Wang 2022], which offers insight into lung cancer research through deep-learning methods. In short, the model consists of a 3D Convolutional Neural Network that collects various lung CT scans. Then, the images are segmented into regions of similar characteristics. The model algorithm then classifies the types of tissues found in the images, distinguishing between malignant or benign kinds of cancer. Taking all of this into consideration, we intend to implement a deep-learning model with high accuracy that can correctly identify whether a tumor is present in a given image of lung tissue.

2 MODEL ARCHITECTURE

For this project, we have chosen a pre-trained model, which "[...] is a saved network that was previously trained on a large dataset, typically on a large-scale image-classification task." [TensorFlow 2023] More especifically, ResNet-50, a Residual Neural Network that has 50 layers. As the amount of layers in a Neural Network increases, so does the difficulty of training it. ResNet-50 allows us to use many layers without experiencing setbacks in the training performance by using "residual blocks," which stack outputs from past layers onto outputs of stacked layers. [Boesch 2023] Considering that it has been previously trained using a big and broad dataset, the expected model will be effective for the classification of images, with a deeply trained network and decent performance. Moreover, we have opted to customize the pre-trained model, as described by the following architecture pipeline:

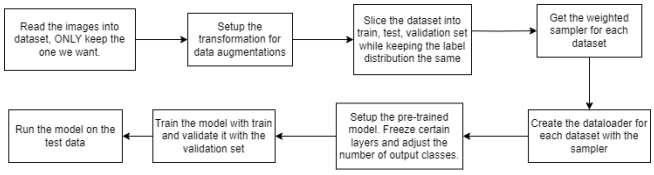

Fig. 1. Visual representation of the model architecture's pipeline

Additionally, we have implemented several modifications to the model in order to improve it. First, we froze the first layer of the model, which will circumvent the destruction of information in the layer as more training cycles happen. [TensorFlow 2023] Then, we changed the learning rate from 0.01 to 0.005 since the loss would skyrocket and become Nan within a few epochs if the learning rate was set too high. Finally, we changed the output feature to 3, as there are only 3 possible labels for the data.

3 DATASET

As for the dataset used for this model, it was retrieved from a Grand Challenge named "WSS4LUAD," which was already labeled by the organizers of the challenge. [Han et al. 2022] The notebook that holds our model will download the data directly from Google Drive. Since the data is about 1.52 GB large, this ensures that the users can just run the notebook without having to worry about where to place the data. Moreover, the notebook will unzip the files during the process. Although the dataset is not evenly distributed, its data is not far spread or too uneven. There are three different labels we need to give to each image, "Tumor," "Stroma," and "Normal." If an image contains a tumor and stroma, then its label will be [1,1,0]. If an image is normal then it will be labeled as [0,0,1]. To make sure all labels are converted to decimal numbers, we converted each label into a binary number and changed it to base 10 format. For example, label [0,0,1] will be converted to 0b001 then 1. Label [1,1,0] will be converted to 0b110 then 6. This process will take place right before the dataset returns the label. We have excluded images with the label '101' and '111' because only 4 images are labeled '101' and only 1 image has the label '111', as well as images containing more than 1 label. Therefore, only images labeled with only stroma, tumor or neither will be included.

For the data augmentation, we applied the following following transformations:

- Flip the image left to right with a 50
- Resize the image to 232pxx232px
- Random crop of 224px
- Convert the image to a tensor
- 50% chance to normalize the color with a mean of [0.485, 0.456, 0.406] and standard deviation of [0.229, 0.224, 0.225].

Regarding possible biases and/or limitations, we do not have the medical background to firmly make better distinctions between to distinguish between the different types of features in the tissue images. As a result, as previously mentioned, we reduced the dataset to only include images that only contain a tumor, stroma, or neither. Additionally, the dataset is not huge for our intended purposes, so we have gathered our sample within our dataset.

4 TRAINING PROCEDURE

Before dwelling on the training process, it is important to note the tools used for its implementation. The model was written in Python using a Jupyter Notebook and several machine learning frameworks, such as Pytorch, Torchvision, and others like numpy and sklearn. Although it can be executed in a web platform, we preferably used Visual Studio Code for a more comfortable and familiar visualization. As for the hardware, the project was ran using the team members' laptops or PCs. For the optimizer, we used a stochastic gradient descent optimizer from Pytorch. We adjusted the learning rate to 0.005. We had previously started with 0.01, but it overfit the model very fast and the loss grew exponentially. We also used 64 as the batch size and we kept the momentum as 0.9. To avoid overfitting, we applied the "early-stopping" technique, which simply consisted of stopping the program at around 21 epochs for the best model. Also, it is important to note that loss became minimal, reducing as more epochs were tested. The following chart displays the qualitative results obtained during the training of our model:

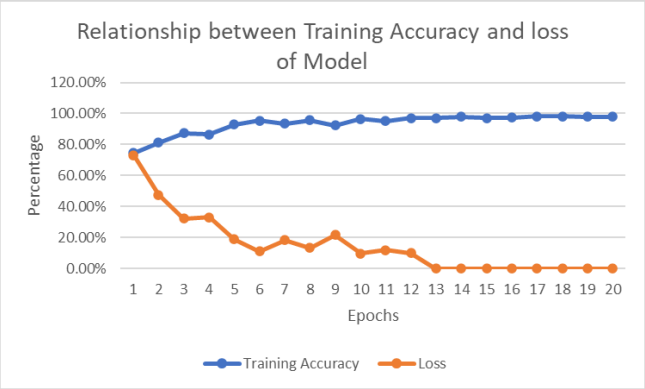

Fig. 2. Line graph showing the relationship between the model's training accuracy and loss

5 EVALUATION PROCEDURE

For the model's evaluation, we used accuracy, loss, sensitivity, specificity, and precision as the metrics to assess its performance when running it against the test set. However, for training and validation, we reduced the metrics to only accuracy and loss in order to minimize the training time.

TABLE I
QUALITATIVE RESULTS OF THE LEADERBOARD (TEST PHASE).

Team name	mIoU	Tumor	Normal	Stroma
ChunhuiLin	**0.8413**	0.8389	**0.8919**	**0.7931**
baseline0412	0.8222	**0.8402**	0.8343	0.7921
Vison307	0.8058	0.8165	0.8554	0.7456
BinghongWu	0.8057	0.8045	0.8654	0.7471
adbertyoungdalu	0.8025	0.7967	0.8668	0.7440
DPPD	0.7815	0.7895	0.8397	0.7153
chenxl	0.7714	0.7897	0.8159	0.7088
sibet0222	0.7609	0.8121	0.7107	0.7599
guoxutao	0.7552	0.8179	0.6840	0.7636
shichuanyexi	0.7411	0.8192	0.6714	0.7325
zyw19990916	0.7382	0.8080	0.6868	0.7196
York	0.7239	0.8023	0.6710	0.6985
akiliyiu@gmail.com	0.7199	0.7557	0.7248	0.6791
Zlin3000	0.7064	0.7493	0.6863	0.6837

Fig. 3. Table showing the qualitative results of the WSSS4LUAD challenge's leaderboard. Via arXiv. ([Han et al. 2022]).

In the paper "WSSS4LUAD: Grand Challenge on Weakly-supervised Tissue Semantic Segmentation for Lung Adenocarcinoma," [Han et al. 2022] there is an overall look into the Grand Challenge's solutions provided by different teams. In this paper, there is a result for all the teams participating in the challenge. We can see the performance of the teams' models and their performance on each label.

However, the participant's models provide a predicted mask to the image and the mIoU is calculated based on the overlap between the actual mask and the predicted mask.

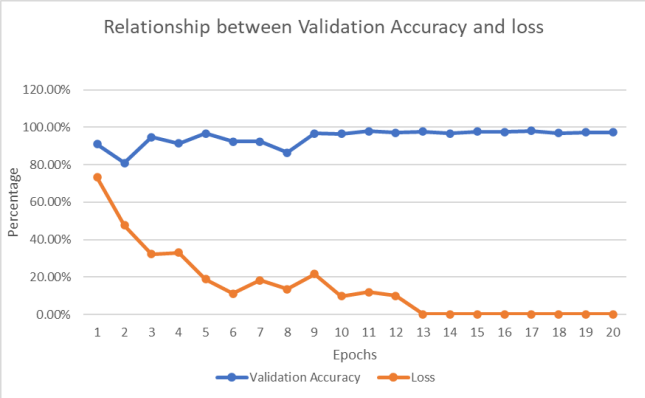

Fig. 4. Line graph showing the relationship between the model's validation accuracy and loss

Here is the graph for the validation accuracy and loss for the 20 epochs we trained on. We can see the accuracy become a straight line at around 9 epochs and the loss dropped close to 0 at around 13 epochs.

6 DISCUSSION

Here is the graph for the validation accuracy and loss for the 20 epochs we trained on. We can see the accuracy become a straight line at around 9 epochs and the loss dropped close to 0 at around 13 epochs.

The data we used for the project only have one of the labels. However, in practice, an image may have multiple labels like tumor and stroma. This means the model works on simple tasks but it might fail as we give more complex images into the model.

I think the result is pretty good. It means that computer vision is capable of identifying images with abnormal cells. The final best model achieves good results in all the metrics (accuracy, loss, sensitivity, specificity, and precision) we used which means it is a solid model for the problems we are solving.

A future direction is to identify images with more than one label for example we also include images with 2 labels in the dataset.

7 CONCLUSION

Definitely, medical imaging integrated with deep learning holds vast potential in the medical landscape. Not only in lung cancer but also in other health issues of a similar nature. In collaboration with researchers, healthcare professionals, and data scientists, algorithms will become more refined, and datasets will become more diverse, resulting in reliable models for timely diagnosis and treatment.

We used a pre-trained model with some layers frozen and we adjusted the learning rate to prevent its loss going to infinity to make sure we have a good result for classifying lung images with different labels. We found out that with some adjustments, the pre-trained vision model can perform very well with our datasets, and lowering the learning rate prevents the infinite loss issue during training.

This will open up more ways for deep-learning models to help classify images in the medical field. It also shows the pre-trained model is capable of helping with image classification in the medical field.

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