

Deep Learning

880663-M-6

Assignment

Using Deep Learning to Perform Multi-Class Classification on the
Lung and Colon Cancer Histopathological
Image Dataset (LC25000)

Report by:

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March 2024

1. Problem Definition

Cancer is a common medical term that can be seen in people's daily lives. Normally, in a healthy body, the cells will reproduce themselves as nearby cells request, but the cancer cells do not follow this pattern and grow their paths to reproduce themselves (Weinberg, 1996). These malignant cells can also transfer to other tissues, and they will form tumors, which could kill people by breaking the needs of organs. It has been a major health issue for years and has been regarded as the leading reason of death (WHO, 2022). In 2020, 10 million deaths occurred because of it (WHO, 2022). Among the types of cancers, lung and colon cancers account for 25 percent of the total cases, and they are the most lethal ones (Masud et al., 2021). Although they are deadly, early detection of cancers can enhance the survival rate, and sometimes it can be fixed by just performing surgery (Schiffman et al., 2015). Thus, efficient diagnosis of cancer becomes crucial. Usually, this work is done by medical experts so it will take time. However, with the coming era of artificial intelligence, this work can be finished with computer vision techniques like deep learning. It enables medical professionals to spend less time and cost diagnosing cancers, and possibly maintain great accuracy or better shown in the research, which may largely benefit society (Masud et al., 2021). Hence, this study will concentrate on detecting various lung and colon cancers with deep learning algorithms.

2. Preprocessing and Exploratory Data Analysis

The data has 25,000 images with 768x768 pixels. These images can be further categorized into 5 classes with 5,000 images respectively: Colon Adenocarcinoma, Colon Benign Tissue, Lung Adenocarcinoma, Lung Benign Tissue, and Lung Squamous Cell Carcinoma. As a start, the images are resized to 120x120 pixels to improve computational efficiency and avoid memory constraints. Then, the target variables are transformed into categorical data with one-hot encoding since they are purely texts and cannot be processed by models (Refer to the preprocessing section in the Jupyter Notebook). The label number and class name are provided for the visualization later (Table 1). Finally, the data will be split into 60% for training, 20% for validation, as well as 20% for the test set with a random seed of 42. As for exploratory data analysis, the class distribution can be seen below in Figure 1. Each class is equally distributed. Random 15 sample images are also visualized in Figure 2.

Figure 1: Distribution of classes

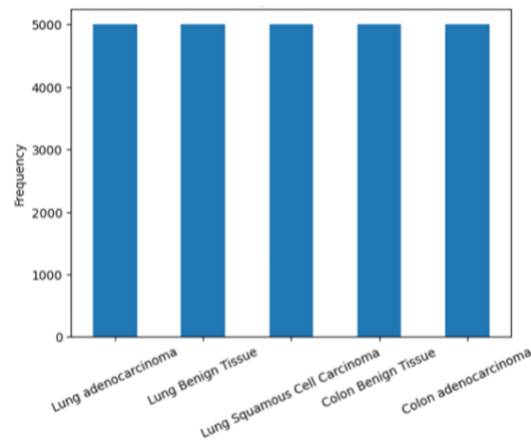


Figure 2: Visualization of sample images

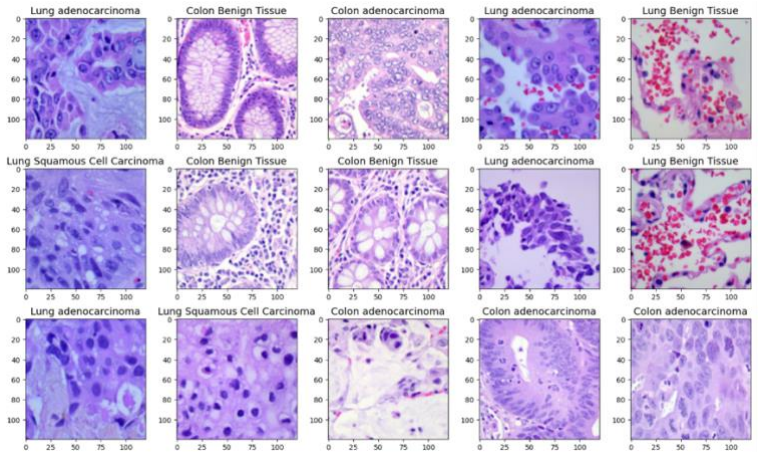


Table 1: Label number and class name

Label Number	0	1	2	3	4
Class Name	Colon Benign Tissue	Colon Adenocarcinoma	Lung Benign Tissue	Lung Squamous Cell Carcinoma	Lung Adenocarcinoma

3. Results of the Baseline Model

In summary, the training losses kept decreasing as the epoch increased while the validation loss fluctuated (Figure 3). Based on the loss graph, the 10th epoch may not be the optimal point since the

validation loss was still decreasing. On the other hand, the training accuracy enhanced as the number of epochs increased and arrived at 81% accuracy. The validation accuracy fluctuated and reached 78% accuracy at the 10th epoch. For Receiver Operator Characteristic (ROC) curve with the Area under the Curve (AUC) on the testing set, the AUCs are all over 90% for each class, which is considered an excellent score (Mandrekar, 2010). In the confusion matrix, on the testing set, the model showed that it could not distinguish between 'Colon Benign Tissue and Colon Adenocarcinoma' as well as 'Lung Squamous Cell Carcinoma and Lung Adenocarcinoma' well. Lastly, on the classification report, the 'recall for Colon Benign Tissue and Lung Adenocarcinoma', and 'precision for Colon Adenocarcinoma' were below 70%, which is worse compared to other classes. The overall accuracy was around 77%. The reasons why these classes are not classified well could be the noise of these images, very similar features in the images, the architecture of this baseline model, imbalanced classes, and more. Imbalanced classes can be excluded first since the classes are equally distributed and more tuning can be conducted to verify the reasons. Overall, the model seemed to have acceptable scores but can be further experimented with more hyperparameter tuning, such as layers, several epochs, and a different filter size to assess if the model has converged or if it can generate a better outcome. It may also benefit from the exploration of more hyperparameter tuning to improve the performance of each class.

Figure 3: Training and validation loss

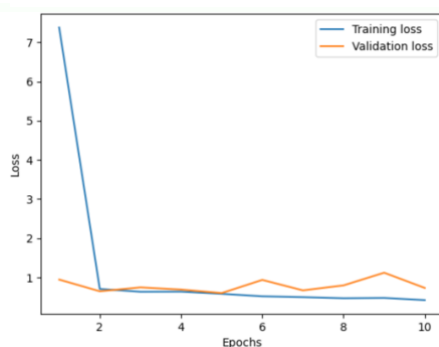


Figure 4: Training and validation accuracy

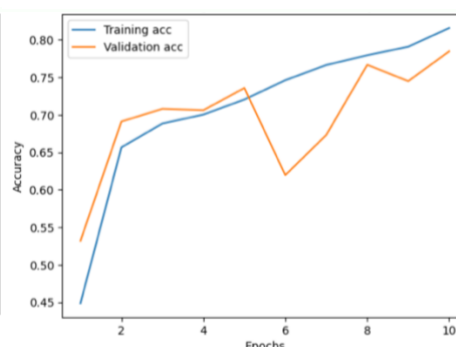


Figure 5: ROC with AUC (Test set)

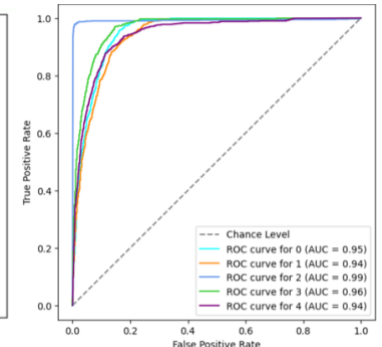


Figure 6: Confusion matrix (Test set)

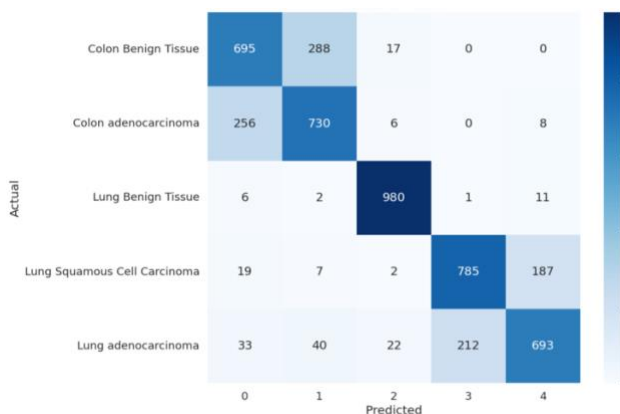


Figure 7: Classification report (Test set)

accuracy 0.7738					
	precision	recall	f1-score	support	
0	0.73	0.68	0.71	1000	
1	0.68	0.73	0.71	1000	
2	0.95	0.98	0.97	1000	
3	0.79	0.79	0.79	1000	
4	0.77	0.69	0.73	1000	
micro avg	0.79	0.77	0.78	5000	
macro avg	0.79	0.77	0.78	5000	
weighted avg	0.79	0.77	0.78	5000	
samples avg	0.77	0.77	0.77	5000	

4. Improved (Fine-tuned) Model and Its Results

To improve the model, some literature is done and used as a groundwork. Based on Sun's research, there are still many challenges for the optimization of neural networks, since people are still quite uncertain about what factors can influence the performance, and many issues cannot be handled properly when using neural networks, which still requires much improvement (Sun, 2020). As for now, for the deep learning community, the common approach is to rely on hyperparameters that usually perform well for image classification problems (Young et al., 2015). Thus, we will rely on the existing architecture that is proven to be effective first and fine-tune some hyperparameters for further improvement as follows.

Proposed architecture based on literature

Firstly, we followed the framework and methodology proposed used in the existing research about lung and colon cancer image classification and adopted them to improve the baseline model (Ananthakrishnan et al., 2023). The reasoning behind the hyperparameters is provided in the discussion section. In the preprocessing step, each image was resized to a smaller size $64*64*3$ and denoised with Gaussian Blur. This processed data enabled the baseline model to hit 84% accuracy on the validation set. Then, the existing layers were replaced by three convolutional layers, two max pooling layers, one flattened layer, and three dense layers. After adding these layers, the model achieved 91%. Next, this model ran 50 epochs since the research shows that 50 and 100 epochs both demonstrate good performance and 50 epochs are more efficient for the experiment (Ananthakrishnan et al., 2023), which demonstrates 92% accuracy on the validation set in our experiments. Finally, drop layers and an early stop were used. The 23rd epoch was adopted in the final model and obtained 95% accuracy and over 99% AUC for each class on the testing set (Figure 9 and Figure 10). In brief, the overall changes are summarized in Table 2 and Figure 8 below. In addition, based on the performance report, this classifier demonstrates quite great performance for each class with about 100% AUC, and the precision, recall, and f1-score are all over 90% (Figure 10). The model makes fewer errors and only cannot identify Lung Adenocarcinoma and Lung Squamous Cell Carcinoma very well, but still has much improvement in detecting each class (Figure 11).

Table 2: Changes for the enhanced model

Changes	Proposed Framework (Ananthakrishnan et al., 2023)
Preprocessing	Resize to a smaller size $64*64*3$ and denoised with Gaussian Blur
Number of layers	12
Used layers	Convolutional Layer Maxpooling Layer Convolutional Flatten Layer Dense Layer Dropout Layer
Number of epochs	50

Figure 8: Summary of enhanced model

Layer (type)	Output Shape	Param #
conv2d_39 (Conv2D)	(None, 62, 62, 32)	896
conv2d_40 (Conv2D)	(None, 60, 60, 64)	18496
max_pooling2d_28 (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_41 (Conv2D)	(None, 28, 28, 128)	73856
max_pooling2d_29 (MaxPooling2D)	(None, 14, 14, 128)	0
dropout_15 (Dropout)	(None, 14, 14, 128)	0
flatten_14 (Flatten)	(None, 25088)	0
dense_42 (Dense)	(None, 256)	6422784
dropout_16 (Dropout)	(None, 256)	0
dense_43 (Dense)	(None, 64)	16448
dropout_17 (Dropout)	(None, 64)	0
dense_44 (Dense)	(None, 5)	325

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Total params: 6532885 (24.92 MB)
Trainable params: 6532885 (24.92 MB)
Non-trainable params: 0 (0.00 Byte)

Figure 9: ROC with AUC (Test set)

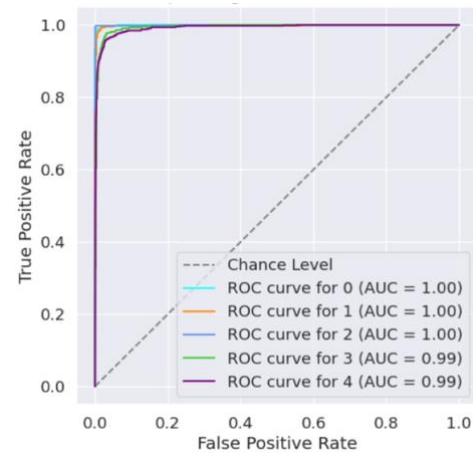


Figure 11: Confusion matrix (Test set)

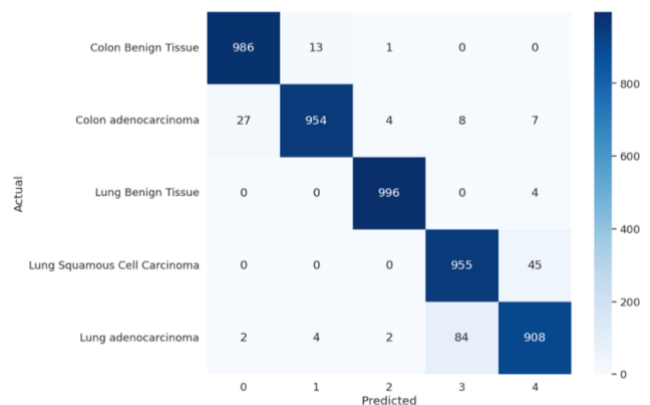


Figure 10: Classification report (Test set)

accuracy 0.9598				
	precision	recall	f1-score	support
0	0.97	0.99	0.98	1000
1	0.98	0.95	0.97	1000
2	0.99	1.00	0.99	1000
3	0.91	0.95	0.93	1000
4	0.94	0.91	0.92	1000
micro avg	0.96	0.96	0.96	5000
macro avg	0.96	0.96	0.96	5000
weighted avg	0.96	0.96	0.96	5000
samples avg	0.96	0.96	0.96	5000

Extended experiment

Based on the proposed architecture, this study also tried other hyperparameters: optimizers, activation functions, regularization, and kernel size. As a start, some literature was done, and it was found that one research utilized RMSprop optimizer, which calculates the average value to optimize algorithms, and obtained over 96% accuracy on the same dataset (Mangal et al., 2020). Thus, this optimizer was adopted to replace Adam, and the result achieved 95% on the validation set. Nevertheless, after applying RMSprop optimizer, the training and validation loss fluctuated sharply and the validation accuracy was much higher than the training one. This optimizer may not be a good option compared to Adam since RMSprop made the performance unstable and it could result from the lack of the benefit of Momentum and different update rules so we continued to use Adam. Next, on this dataset, many research papers used relu for the intermediate layers and softmax for the output layers (Al-Mamun Provath et al., 2023; Hadiyoso et al., 2023; Hage Chehade et al., 2022; Mangal et al., 2020). The strength of relu is to introduce linearity, avoid vanishing gradient issues, and enable the model to learn quickly. On the other hand, it is reasonable to apply softmax in the final layer since the task is a multi-classification problem and this function helps to find the corresponding classes. Hence, the activation function of the baseline model seemed to be the best choice already. However, this study still experimented with the common activation functions: sigmoid and tangent. The results showed 81% and 20% accuracy on the validation set for tangent and sigmoid activation functions respectively. Since these activation functions made the accuracy decrease dramatically, this study continued to use relu. As for the filter size, many research papers used 3x3 as the filter size for this dataset and acquired quite great results (AlGhamdi et al., 2023; Ananthakrishnan et al., 2023; Talukder et al., 2022) while some research only used 11x11 in the first layer and 3x3 for the rest, which leads to great outcomes too (Hamed et al., 2023a, 2023b). As a result, 11x11 was included in this study. The final result showed that the accuracy remains at 20% on the validation set, so we go back to 3x3 for the first layer. Lastly, some research adopted different regularization methods: kernel_regularizer(L2), bias_regularizer(L1), and activity_regularizer(L1) with regularization parameters 0.016, 0.006, and 0.006 respectively (Singh et al., 2024). Because dropout layers were applied in our enhanced model for regularization, we removed the dropout layer and used regularizers to see if the performance improved. After applying it, the accuracy arrived at 88% on the validation set when the number of epochs was 23. In the end, we utilized an early stop to choose the optimal point, which is the 17th of the epoch. The final results obtained 89% accuracy on the testing set, and all the precision, recall, and f1-score are all above 80%. For the AUC, each class had over 98%. Since this model did not generate better performance, the proposed architecture in Ananthakrishnan's research in the previous step is more recommended in colon and lung image classification tasks (Ananthakrishnan et al., 2023). Due to the limitation of the page, please refer to the Extended experiment in Enhanced Model section in the notebook file for ROC curve, performance report, and confusion matrix.

5. Transfer Learning Model and Its Results

Transfer learning is a technique in machine learning that enables people to utilize a pre-trained model for other predictions, especially in computer vision and natural language processing domains. Usually, this method is needed when the target training data is insufficient or costly to collect; it can solve this issue by using relevant datasets with availability (Weiss et al., 2016). One research indicates that this approach will benefit many domains and can possibly enhance the model performance (Pan and Yang, 2009). There are many common transfer learning models, such as VGG16, InceptionV3, and ResNet50. In this assignment, VGG16 was adopted since it has shown pretty great performance on this dataset in other research (Tammima, 2019). In the study, VGG16 and data augmentation were used to achieve 95% accuracy, so we referred to the methodology in the research and provided the reasoning in the discussion section. As a start, VGG16 model was frozen and three dense layers were added after it: two with relu activation function (4096 units) and one softmax function (5 units) (Tammima, 2019). Also, 20 epochs were utilized due to the great performance in the previous research (Tammima, 2019). However, due to memory constraints, data augmentation was not conducted. The model summary can be found below (Figure 15). Finally, the model achieved 96% accuracy and

showed overfitting at the 20th epoch. After applying an early stop, the model obtained almost 97% accuracy (Figure 14) and the AUCs all achieved 100% for each class on the testing set (Figure 12), which is regarded as outstanding performance (Mandrekar, 2010). From the confusion matrix (Figure 13), it can be seen that most classes were classified well but the model may have slight difficulty distinguishing between Lung Adenocarcinoma and Lung Squamous Cell Carcinoma as well.

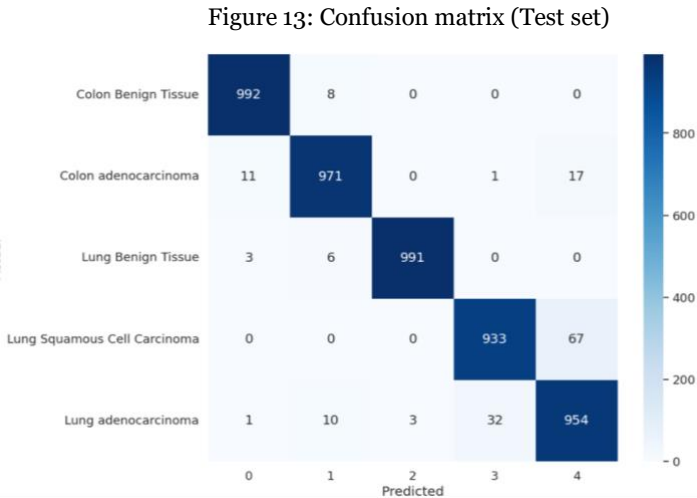
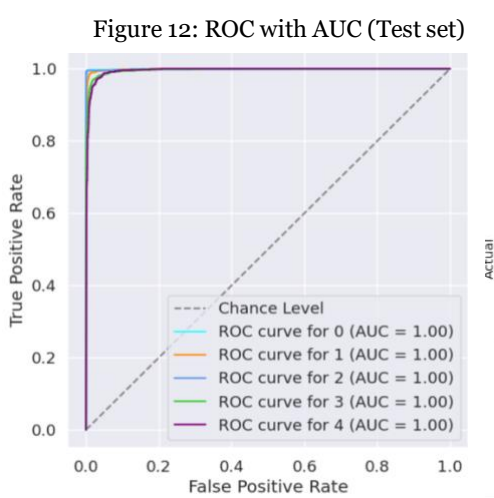


Figure 14: Classification report (Test set)

accuracy	0.9682				
	precision	recall	f1-score	support	
0	0.99	0.99	0.99	1000	
1	0.98	0.97	0.97	1000	
2	1.00	0.99	0.99	1000	
3	0.97	0.93	0.95	1000	
4	0.92	0.95	0.94	1000	
micro avg	0.97	0.97	0.97	5000	
macro avg	0.97	0.97	0.97	5000	
weighted avg	0.97	0.97	0.97	5000	
samples avg	0.97	0.97	0.97	5000	

Figure 15: Model summary

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 2, 2, 512)	14714688
flatten_2 (Flatten)	(None, 2048)	0
dense_6 (Dense)	(None, 4096)	8392704
dense_7 (Dense)	(None, 4096)	16781312
dense_8 (Dense)	(None, 5)	20485
Total params: 39909189 (152.24 MB)		
Trainable params: 25194501 (96.11 MB)		
Non-trainable params: 14714688 (56.13 MB)		

6. Discussion

The techniques used in the enhanced model, and transfer learning model

For the enhanced model, each image was resized and denoised with Gaussian Blur in the pre-processing step (Ananthakrishnan et al., 2023). According to Semma et al.'s research, large image size will take more time and resources to train, and resizing can mitigate this problem but it can impact model performance positively or negatively; the influence of image size can vary for different tasks (Semma et al., 2021). In Ananthakrishnan et al.'s study, 64*64 showed good results so it is considered one of the good options. On the other hand, noise is usually one obstacle for image classification, and removing it is an important step in optimizing models (Balafar, 2012). The improvement of the model can be seen in the previous section and Ananthakrishnan et al.'s study. After using this method, both the loss of training and validation decreased and the accuracy of training and validation increased over epochs, which shows the model is generalizing well to unseen data and may not have overfitting or underfitting problems. Later, more layers were used to replace the existing layers in the baseline model because increasing the hidden layers can enhance the accuracy through more training, which also increases the model complexity (Uzair & Jamil, 2020). Usually, the common approach is to begin with a few hidden layers and then increase more layers until the loss of validation starts decreasing but we followed the existing architecture here. Then, the model had overfitting problems at the 10th epoch since the training loss was lower and the training accuracy was much higher than the validation set. Although it can be seen that the lowest validation loss was in the 4th epoch, it would be too early to use an early stop since it could be a local minimum

and the loss of validation could still go down. Hence, 50 epochs were used to see if the loss of validation set had a decreasing or increasing trend and how the accuracy plots went. Then, the model indeed demonstrated obvious overfitting at the 50th epoch because the validation loss rose dramatically, and validation accuracy was much lower than the training one; therefore, drop layers were adopted for regularization. Now, the model seems to show the optimal point at the 23rd epoch since the loss of validation kept decreasing before the 23rd epoch. After the 23rd epoch, the validation loss kept increasing. Consequently, an early stop was adopted here to choose the optimal spot to get the best-performing model. Finally, we obtained the well-performing model through the hyperparameter-tuning. Compared to the baseline model, the accuracy, precision, recall, f1-score, and AUCs all improve greatly. Based on the confusion matrix, the enhanced model makes fewer mistakes and can almost classify each class perfectly. More importantly, this model can distinguish Colon Benign Tissue and Colon Adenocarcinoma effectively.

As for the transfer learning model, VGG16 model was used. Including top function was set to false here, and this allowed the model to train the new layer but not change the weights of the models. Thus, the new layers could learn from extracting features from VGG16 model. After that, two dense layers were added. The reason why dense layers were utilized is because they could combine the weight of input features and enable the model to learn more from the data (Baeldung, 2023), which could increase the model performance. They also introduced non-linearity to let models learn more complex patterns. Finally, the last layer still used softmax as an activation function because it was a multiclass classification problem for five classes. The final model got great accuracy (96%) but was a bit overfitting since the validation began boosting and training accuracy was much better than the validation set. So an early stop was also adopted in the end to avoid overfitting. In contrast to the baseline model, the outcome of this model demonstrated excellent scores in terms of accuracy, precision, recall, f1-score, and AUCs. This model could not identify Lung Adenocarcinoma and Lung Squamous Cell Carcinoma well too but still a lot much better than the baseline model.

Future research

Due to the limited resource usage and time constraints, this research did not further improve the model. However, in addition to the hyperparameter tuning above, it is recommended to include the following tuning steps in future research, and the reasons are explained below as well: Batch Normalization, Learning Rate, Other Transfer Learning Models, and Hybrid System Hybrid Systems. To begin with, according to Bjorck et al.'s research, performing batch normalization tends to enhance the accuracy and shorten the time for training since batch normalization will allow the training with larger learning rates, leading to quick convergence and great generalization (Bjorck et al., 2018). As for the learning Rate, if it starts at a small rate, it will make the learning slow and take much time to find the optimum; on the other hand, if the learning rate is too high, it may oscillate and miss the optimum point in the end (Iosifidis & Tefas, 2022). Therefore, the learning rate plays an important role in model optimization and should be explored if possible. Moreover, different transfer learning models can be adopted and explored to improve the model performance. For instance, for the same dataset, some researchers have used ResNetv2 (Baranwal et al., 2022), AlexNet (Mehmood et al., 2022), and ResNet50 (Ananthakrishnan et al., 2023) to achieve 99.7%, 98.4%, and 100% accuracy respectively. Besides, hybrid systems can be taken into consideration as well. For example, in Al-Mamun Provath et al.'s research, features are extracted with neural networks (VGG-19) and combined with handcrafted variables to achieve a great accuracy of 99.64% (Al-Mamun Provath et al., 2023). In addition, this author also tried to adopt fusion features of GoogLeNet and VGG-19, but not the best outcome. Hence, hybrid systems are recommended for exploration as well (Al-Mamun Provath et al., 2023). Lastly, data augmentation, such as rotation, flipping, scaling, cropping, and adding noise, can be considered too. Based on past experiments, it is known that Lung Adenocarcinoma and Lung Squamous Cell Carcinoma cannot be distinguished easily by both models. Conducting data augmentation may help the model generalize better to unseen data and can enhance its ability to differentiate between similar classes (Mikołajczyk & Grochowski, 2018).

7. References

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