

Lung Cancer Cell Classification Using Deep Learning Models

submitted by

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To Whom It May Concern

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I hereby declare that this project report entitled "Lung Cancer Cell Images Classification Using Deep Learning Models" is an outcome of my genuine and independent work, as part of my Master of Computer Application program.

All information in this document has been obtained and presented in accordance with academic rules and ethical conduct.

I also declare that, as required by these rules and conduct, all materials and results that are not original to this work have been fully cited and referenced.

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Abstract

This project report explores the application of Convolutional Neural Networks (CNNs) and transfer learning for the detection and classification of lung cancer using histopathological images. Lung cancer is a leading cause of cancer-related deaths worldwide, and early, accurate detection is critical for effective treatment. This study leverages the ResNet50 architecture, a state-of-the-art CNN model, to classify lung cancer images. Transfer learning techniques are employed to fine-tune the pre-trained ResNet50 model, enhancing its performance with the lung cancer dataset. Rigorous hyperparameter tuning and model evaluation were conducted to optimize detection accuracy, precision, recall, and F1-score. The experimental results demonstrated that the ResNet50 model achieved superior performance compared to other models, indicating its effectiveness in accurately detecting lung cancer. This research underscores the potential of advanced CNN architectures in improving lung cancer diagnostics and suggests future work integrating additional imaging modalities and sophisticated data augmentation techniques.

Chapter 1

Introduction

The prevalence of lung cancer continues to pose a significant health challenge globally, being one of the leading causes of cancer-related deaths. It is estimated that lung cancer accounts for nearly 25% of all cancer fatalities[1], with the primary risk factor being smoking, responsible for about 80% of cases. Other contributors include exposure to radon, second-hand smoke, air pollution, and hazardous occupational environments[2]. Diagnosing lung cancer accurately and swiftly is critical for improving patient outcomes and survival rates.

Malignant growth is described as a collection of related disorders characterized by abnormal cell development that continuously spreads into surrounding tissues. According to global disease statistics, various cancer types can occur in human bodies [3]. Lung and colon cancers are among the most common, with lung cancer ranking first in men and third in women, and colon cancer ranking third in men and second in women. The primary causes of lung cancer are tobacco use and smoking, while the causes of colon cancer include older age, smoking, and regular consumption of red meat. Lung cancer subtypes include lung adenocarcinoma, lung squamous cell carcinoma, and colon adenocarcinoma [4], identified through histopathology, the study of tissues using a microscope. A histopathology report, known as a biopsy report, enables doctors to identify cancer subtypes and their stages. The characteristics and treatments of different pathological subtypes of cancer vary significantly. However, an accurate and timely prognosis can lead to a compelling treatment plan and improve patient survival.

1.1 Traditional Diagnosis Methods

Traditionally, lung cancer diagnosis involves a series of imaging techniques such as x-rays and CT scans, coupled with sputum cytology and tissue biopsies. Pathologists play a crucial role in examining histopathological slides to identify cancerous cells and determine the specific type of lung cancer. This manual examination process is not only time-consuming but also subject to human error, which can lead to misdiagnosis and inappropriate treatment plans, adversely affecting patient health.

1.2 Benefits of Applying CNNs and Transfer Learning

In recent years, the integration of machine learning (ML) and deep learning (DL) techniques into medical diagnostics has shown promising potential in addressing these challenges. Machine learning, a subset of artificial intelligence (AI), enables systems to learn from data and improve their performance on specific tasks without explicit programming. Among the various ML techniques, Convolutional Neural Networks (CNNs) have emerged as a powerful tool for image analysis, capable of detecting intricate patterns and features that may be overlooked by human eyes.

This project focuses on utilizing CNNs combined with transfer learning to enhance the detection and classification of lung cancer from histopathological images. The dataset employed in this study, available on Kaggle, consists of diverse histopathological images of lung cancer, providing a robust foundation for training and validating the deep learning models.

Transfer learning, a method where a pre-trained model is adapted to a new but related task, offers several advantages in this context. By leveraging models that have already been trained on large image datasets, we can significantly reduce the time and computational resources required for training while also improving the model's performance. This

approach is particularly beneficial in medical imaging, where labeled data can be scarce and expensive to obtain.

Applying CNNs and transfer learning to lung cancer histopathological images presents multiple benefits. Firstly, these models can process and analyze large volumes of data quickly and with high accuracy, potentially surpassing the diagnostic capabilities of human experts. This leads to faster diagnosis, allowing for earlier intervention and treatment. Secondly, automated systems provide consistent and objective results, reducing the likelihood of human error and ensuring that patients receive appropriate care based on accurate diagnoses.

1.3 Objective

Lung cancer detection has become increasingly crucial with the advancements in medical imaging technologies and the growing incidence of lung cancer worldwide. Early and accurate detection is essential for effective treatment and improved patient outcomes. In response to these needs, our project aims to leverage the power of convolutional neural networks (CNNs) and transfer learning to enhance lung cancer detection capabilities.

Lung cancer remains one of the leading causes of cancer-related deaths globally. The complexity and variability of lung cancer manifestations in medical images pose significant challenges for traditional diagnostic methods. The introduction of deep learning, particularly CNNs, offers a promising solution by automating and improving the accuracy of lung cancer detection from imaging data.

This project focuses on the following objectives:

1. Implementing State-of-the-Art CNN Models: Utilizing the ResNet50 architecture, a powerful and widely recognized CNN model, to classify lung cancer images. The

model's deep architecture and residual connections are expected to handle the intricate patterns and features present in medical images effectively.

2. **Leveraging Transfer Learning:** Employing transfer learning techniques to fine-tune the pre-trained ResNet50 model on lung cancer datasets. This approach capitalizes on the model's pre-existing knowledge from large image datasets, enhancing its performance and reducing the need for extensive labeled medical data.
3. **Optimizing Detection Accuracy:** Conducting rigorous hyperparameter tuning and model evaluation to achieve high accuracy, precision, recall, and F1-score. Ensuring the model's robustness and reliability in differentiating between malignant and non-malignant cases.

By achieving these objectives, this project aims to make a significant contribution to the field of medical imaging and lung cancer detection, offering a reliable and efficient tool for early diagnosis and potentially saving lives through timely intervention.

1.4 Organization of the Project Work

Chapter 1: Introduction

This chapter introduces the critical issue of lung cancer diagnosis, emphasizing its prevalence and the challenges associated with current diagnostic methods. It sets the context for the project by highlighting the potential of deep learning techniques, particularly Convolutional Neural Networks (CNNs), in enhancing the accuracy and speed of lung cancer detection from histopathological images. The objectives of the project are outlined, focusing on the application of CNNs and transfer learning to improve diagnostic accuracy.

Chapter 2: Literature Review

This chapter provides a comprehensive review of the existing literature on lung cancer detection and classification using histopathological images. It covers traditional diagnostic methods and the evolution of machine learning and deep learning approaches in medical imaging. Special attention is given to the use of CNNs and the role of transfer learning in improving the performance of models in medical diagnostics.

Chapter 3: Methodology

This chapter explains the theoretical concepts underlying the study, including an introduction to Convolutional Neural Networks (CNNs) and transfer learning. It details the methodology adopted for the project, describing the dataset sourced from Kaggle, the preprocessing steps to standardize the images, and the implementation of the ResNet50 model and EfficientNetB3 model. The chapter also covers the fine-tuning process of the pre-trained model to adapt it to the lung cancer dataset.

Chapter 4: Experiments and Results

This chapter presents the experiments conducted in the project. It describes the training and validation processes of the ResNet50 model on the histopathological image dataset. The performance of the model is analyzed using various metrics, including classification accuracy and loss. The results are compared with other models to demonstrate the effectiveness of the proposed approach.

Chapter 5: Conclusion and Future Work

This chapter discusses the findings of the project, highlighting the strengths and limitations of the approach used. It concludes with suggestions for future research, including further fine-tuning techniques, the exploration of other CNN architectures, and the potential for applying the model to other types of cancer datasets to enhance its robustness and performance.

Chapter 2

Literature Review

The authors W. Ausawalaithong, A. Thirach, S. Marukatat, and T. Wilaiprasitporn [11] used deep learning with a transfer learning approach to predict lung cancer from the chest X-ray images obtained from different data sources. Image size of 224X224 with 121-layer Densely Connected Convolutional Network (DenseNet-121) and a single sigmoid node was applied in a fully connected layer. The proposed model achieved $74.43 \pm 6.01\%$ mean accuracy, $74.96 \pm 9.85\%$ of mean specificity, and $74.68 \pm 15.33\%$ mean sensitivity for different image source dataset.

T. Atsushi, T. Tetsuya, K. Yuka, and F. Hiroshi [12] applied Deep Convolutional Neural Network (DCNN) on cytological images to automate lung cancer type classification. They considered Small cell carcinoma, Squamous cell carcinoma, Adenocarcinoma images in their dataset. The DCNN architecture of 3 convolution and pooling layers and 2 fully connected layers with dropout of 0.5 were used. The model developed was able to achieve an overall accuracy of 71.1%, which is quite low.

W. Rahane, H. Dalvi, Y. Magar, A. Kalane, and S. Jondhale [13] proposed using image processing and machine learning (Support Vector Machine) for lung cancer detection on computed tomography (CT) images. Image processing like grayscale conversion, noise reduction, and binarization was carried out. Features like area, perimeter, and eccentricity from the segmented image region of interest were fed to the support vector machine (SVM) model.

M. Šarić, M. Russo, M. Stella, and M. Sikora [14] proposed CNN architectures implementing VGG and ResNet for lung cancer detection using whole slide histopathology images, and the output was compared using the receiver operating characteristic (ROC) plot. Patch level accuracy of 0.7541 and 0.7205 was obtained for VGG16 and ResNet50

respectively which is quite low. The authors explained that the given models' low accuracy was due to large pattern diversity through different slides.

The authors S. Sasikala, M. Bharathi, B. R. Sowmiya [15], proposed using CNN on CT scan images to detect and classify lung cancer. They used MATLAB for their work and had two phases in training to extract valuable volumetric features from input data as the first phase and classification as the second phase. Their proposed system could classify the cancerous and non-cancerous cells with 96% accuracy.

SRS Chakravarthy, R. Harikumar [16], used CoOccurrence Matrix (GLCM) and chaotic crow search algorithm (CCSA) for feature selection on computed tomography (CT) and applied probabilistic neural network (PNN) of the classification task. They found that the PNN model built on CCSA features performed better with 90% accuracy.

Jiang et al. [20] created a two-dimensional CNN architectures for tumor or spot detection. They used images with vascular characteristics. Setio et al. [21] employed 2D CNN architectures to locate lung cancer. CT scans with several planner perspectives were used as training data. Several lung nodule identification techniques were combined using CNNs to improve the result.

Methodology

Our proposed system followed dataset acquisition, preprocessing, model training, testing, and prediction to classify lung histopathology images using a proposed CNN, fine-tuned ResNet50 and EfficientNetB3 models, described in the below sections.

3.1 Dataset acquisition

The dataset used in this research is taken from the Lung and Colon Cancer Histopathological Image LC25000 image dataset [17], which consists of 25,000 images with two subfolders: colon cancer folders containing 10,000 images and lung cancer folders with 15,000 images. All images are in JPEG format and are 768×768 pixels in size. The lung cancer folder contains three subfolders with two lung cancer types and benign lung tissue images. From histopathology images, cancerous and noncancerous can be identified as follows:

1. Malignant tissue: It can be identified as dark in color and abnormal nuclei tissue growth compared to its normal tissue image.
2. Benign tissue: This region has normal growth of tissues and is light in color.

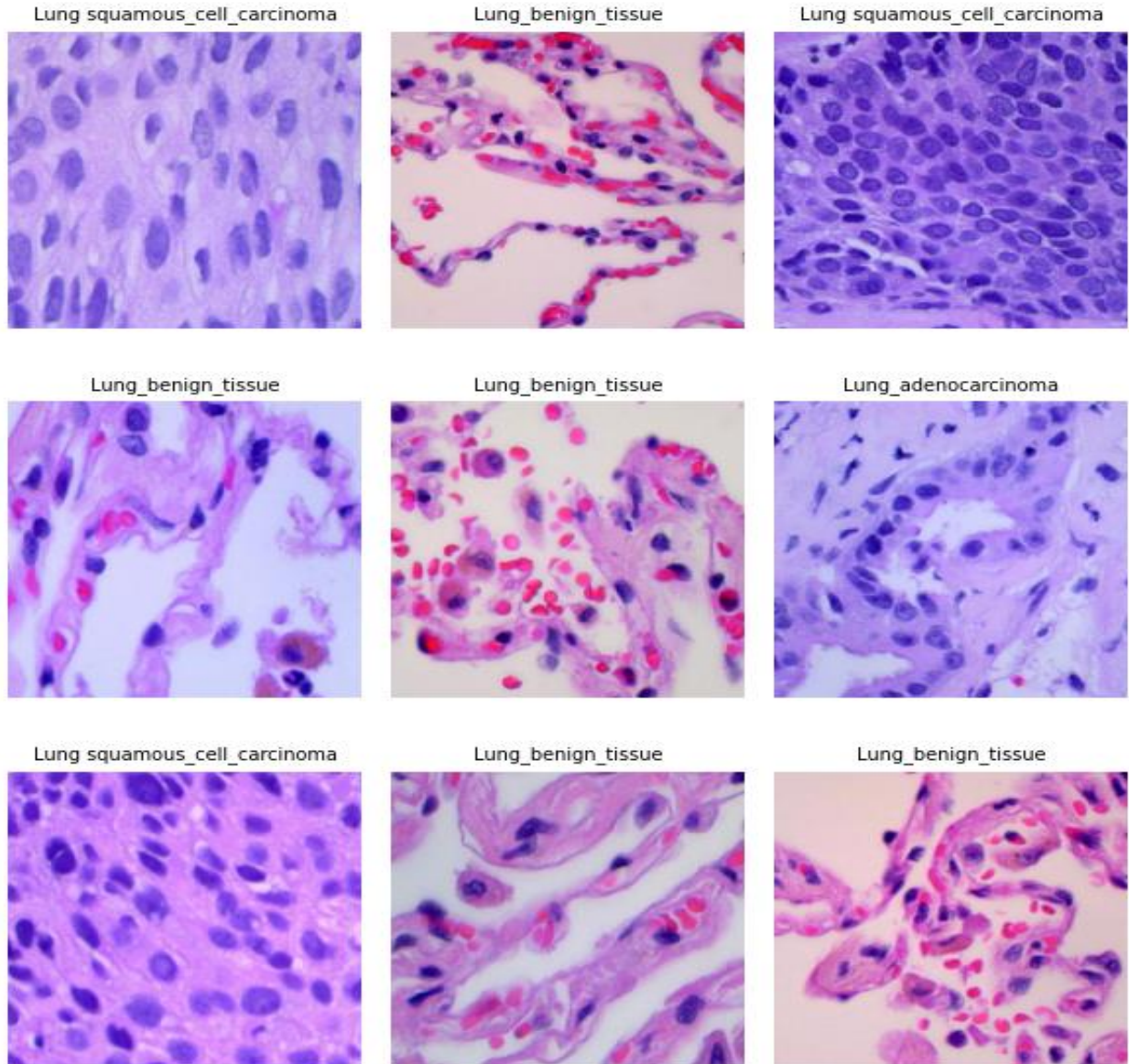


Figure 3.1-Image samples from LC25000 dataset image.

Three functions are applied to augment the images, as explained in [22]; the first function is rotated randomly between 25% on the right and 25% on the left. The second function adds random noise to the images, and the third function is horizontal flips, which flips the image array of pixels. Using these augmentation functions, the images in the dataset are expanded for lung cancer images up to 15,000. So, in this research, the five classes, lung adenocarcinoma, lung squamous cell carcinomas, benign lung tissue, colon adenocarcinoma, and colon benign tissue, are considered to be classified. Each class

contains 5,000 images. The same for colon images; make 10,000 images, each of the two categories having 5,000 images, but for this project, we focus on the lung tissue images.

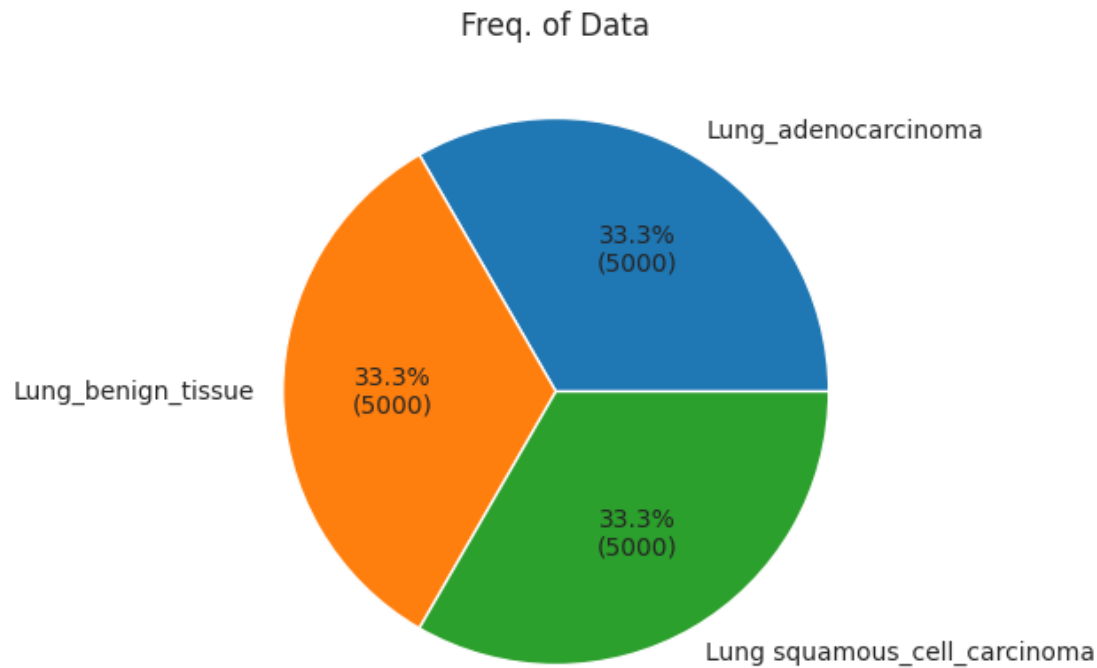


Figure 3.2-Class distribution of LC25000 dataset

3.2 Preprocessing

In the preprocessing phase, we have to ensure that all images are equal in size for the best result of the CNN model. In the first step, all images are in 768×768 pixels. We adjusted the image resolution size into equal sizes of 224×224 pixels for all training, validation, and testing stages. To avoid the imbalanced problem, the classification of classes is not balanced; that is, one class has more images than all other classes, so we must have an equal number of images in each class. That is why each class has an equivalent of 5,000 images in our dataset. A straightforward way to deal with surviving class irregularities in model learning is to resample the training data (a premeasure).

3.3 Dataset Splitting

The dataset was divided into training, validation, and testing sets with a typical split of 80% for training, 10% for validation, and 10% for testing. This ensured that the model was trained on a large portion of the data while maintaining sufficient data for validation and testing to evaluate model performance accurately.

Found 12000 validated image filenames belonging to 3 classes.

Found 1500 validated image filenames belonging to 3 classes.

Found 1500 validated image filenames belonging to 3 classes

3.4 Transfer learning

Transfer learning is a mainstream approach in computer vision-related problems; hence, we combined the pretrained models with the newly trained layer of CNN architecture. Here, we are using deep learning pre-trained EfficientNetB3 and ResNet50 models, where the last layer of the model performs as input data to another classifier. In addition, we utilized the ImageNet dataset for transfer learning techniques for classification, which helped us achieve better performance accuracy and saved training time. It can be seen that the previous model that was trained on source data is combined with the newly trained target data model with the help of transfer learning.

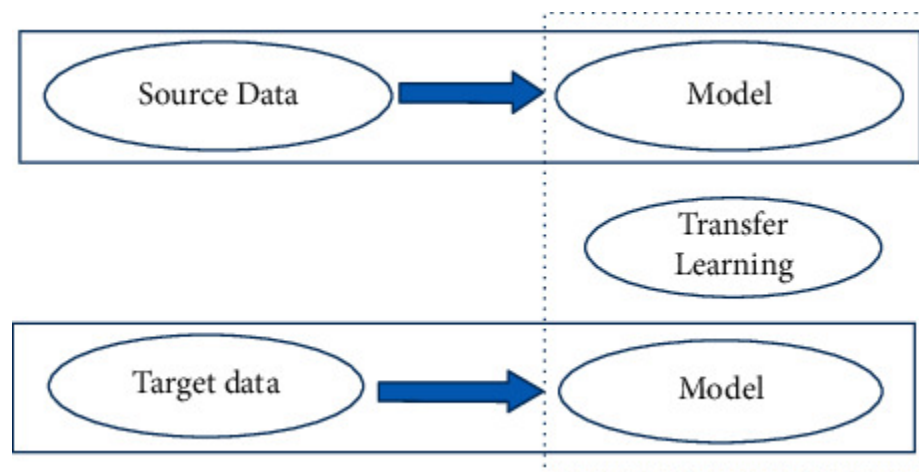


Figure 3.3-Transfer learning schematic diagram.

3.5 Convolutional Neural Network

The structure of any Convolutional Neural Network (CNN) is made up of convolutional layers, pooling layers, and fully-connected layers, including dense layers. The descriptions of the layers are presented below.

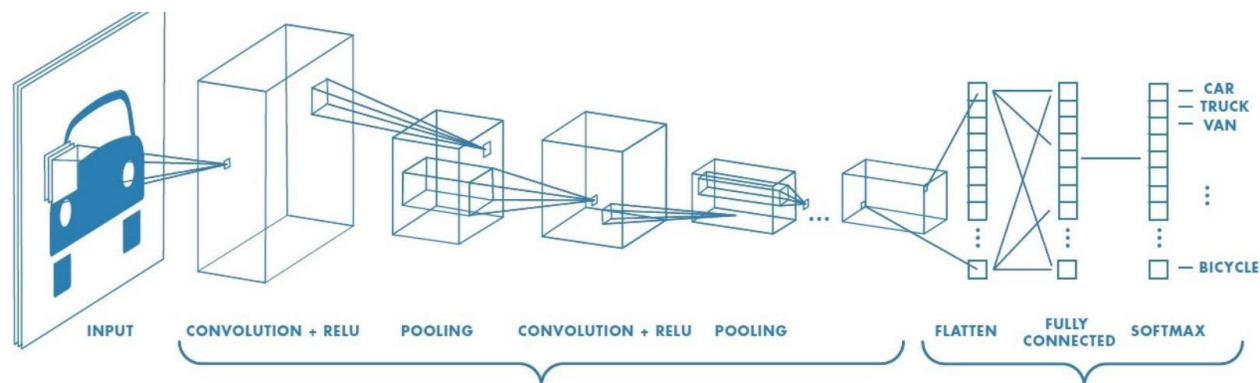


Figure 3.4- Architecture of a CNN [23]

3.6 Architecture of proposed CNN model

A linear stack of layers was used to create the Convolutional Neural Network (CNN) for image classification and recognition in this project. The model architecture comprises multiple convolutional layers with kernel filters, max pooling layers, and fully connected (dense) layers. The softmax function is applied in the output layer to classify the given lung tissue images into three categories: benign, adenocarcinoma, and squamous cell carcinoma.

The dataset was split into training, validation, and test sets with an 80-10-10 ratio, respectively. Images of size 224x224 pixels were passed to the input layer. Convolutional layers applied a kernel matrix of (3, 3) with ReLU activation to extract features. Max pooling with a pool size of (2, 2) was used to reduce the spatial dimensions and computational parameters. Batch normalization layers were included to stabilize the training process.

After the convolutional layers, a flatten layer converted the 2D matrix into a 1D vector, which was then passed through dense layers. Dropout layers with rates of 0.5, 0.3, and 0.2 were used in the dense layers to prevent overfitting. The final output layer used a softmax activation function to provide class probabilities.

The model was compiled using the Adamax optimizer with a learning rate of 0.001 and the categorical cross-entropy loss function, which calculates the discrepancy between the predicted output and the labeled output. The model was trained for 20 epochs and evaluated using accuracy as the performance metric.

3.7 Resnet50

One of the most well-known ResNet architectures is ResNet50, which consists of 50 layers and achieved state-of-the-art performance on the ImageNet dataset in 2015. ResNet50 consists of 16 residual blocks, with each block consisting of several convolutional layers with residual connections. The architecture also includes pooling layers, fully connected layers, and a softmax output layer for classification.

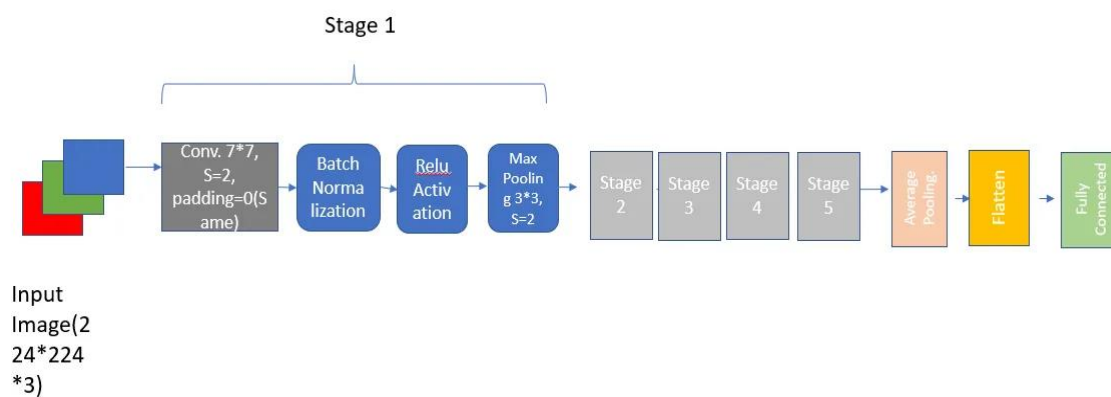


Figure 3.5-ResNet50 CNN Model [26]

3.8 Architecture of fine-tuned ResNet50 model

The project employed the ResNet50 architecture, a well-established convolutional neural network (CNN) model, for an image classification task. The ResNet50 model was

initialized with pre-trained weights from the ImageNet dataset, ensuring a robust starting point for feature extraction and learning. By excluding the final classification layers of the ResNet50 model, customization was facilitated to tailor the model specifically to the project's classification requirements.

Custom layers were added on top of the base ResNet50 model to fine-tune its performance. These included a Global Average Pooling layer for dimensionality reduction and feature aggregation, Batch Normalization layers for improving training stability and convergence, and dense blocks with varying units and dropout rates for feature extraction and regularization. The final output layer utilized a Dense layer with softmax activation, suitable for multi-class classification tasks.

The model was compiled using the Adamax optimizer with a carefully chosen learning rate, optimizing the training process for model convergence. The categorical cross-entropy loss function was utilized to measure the discrepancy between predicted and actual class labels during training. Additionally, a suite of evaluation metrics including accuracy, recall, precision, and F1 score were employed to assess the model's performance comprehensively.

The training process spanned multiple epochs, during which the model learned from the training data and adjusted its weights accordingly. Validation data were used to evaluate the model's performance on unseen data and prevent overfitting. The training process was conducted without shuffling the data, ensuring consistent data order during training iterations for stable model training and evaluation.

3.9 EfficientNetB3

The EfficientNet models [24] depend on straightforward and compelling compound scaling strategies. EfficientNets are a group of neural organization structures delivered by Google in 2019, planned by an enhancement methodology that amplifies the precision for a given computational expense. EfficientNets are suggested for characterization errands. They beat numerous organizations (such as DenseNet, Inception, and ResNet) on the ImageNet

benchmark while running quicker. This strategy empowers the scaling up of a benchmark ConvNet to any objective asset imperative while maintaining model proficiency, which is utilized for moving learning datasets. As a rule, EfficientNet models accomplish higher precision and better productivity over existing CNNs, for example, AlexNet, ImageNet, GoogleNet, and MobileNetV2. Specifically, EfficientNet explores the focal inquiry: is there a standard technique to scale up ConvNets to accomplish better exactness and productivity? In this model, observational investigation is essential to adjust all measurements of organization width (more filters in the layer), depth (more layers), and resolution (more $H * W$); such equilibrium can be accomplished by essentially scaling each of them with steady proportion. This model is a basic yet powerful compound scaling strategy in light of this perception. Unlike all traditional models that scale any of these elements, our approach consistently scales network width, depth, and resolution with a bunch of fixed scaling coefficients.

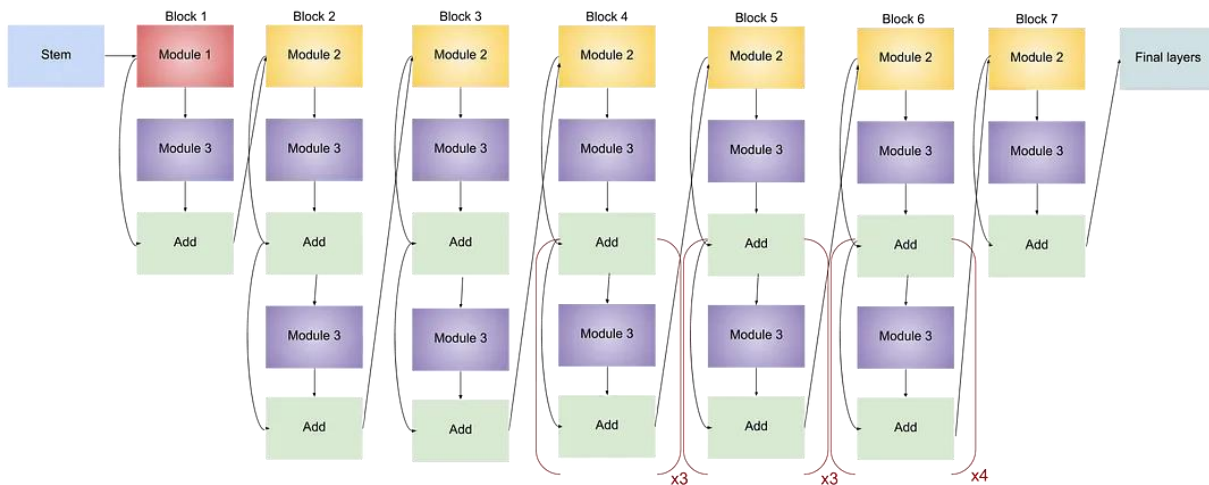


Figure 3.6-Architecture for EfficientNet-B3 [25]

3.10 Architecture of fine-tuned EfficentNetB3 model

In this project's deep learning architecture for image classification and recognition, the EfficientNetB3 model was utilized as the base architecture. EfficientNetB3 is a state-of-the-art convolutional neural network (CNN) architecture that is pre-trained on the

ImageNet dataset. By setting `include_top=False`, the final classification layers are excluded, allowing for customization and addition of custom layers suited to the project's requirements. The input shape of the images is defined as `(224, 224, 3)`, denoting the image size and channels.

Following the base model setup, a series of custom layers were added to fine-tune the EfficientNetB3 model. These layers include a Global Average Pooling layer to reduce dimensionality, Batch Normalization for stabilizing the training process, and multiple dense blocks with varying units and dropout rates for feature extraction and preventing overfitting. The final output layer consists of a Dense layer with softmax activation, tailored to classify images into a specific number of classes represented by `class_counts`.

The resulting model, named `EfficientNetB3_model`, is defined as a `Model` with the specified input and output layers. This architecture showcases the integration of a powerful pre-trained model with additional custom layers, optimizing the model's performance for image classification tasks. The model's compilation utilizes the Adamax optimizer with a learning rate of 0.0001, categorical cross-entropy loss function, and metrics such as accuracy, recall, precision, and F1 score for evaluation over a training period of 20 epochs.

The implementation was carried out using TensorFlow and Keras, and the training was conducted on a GPU to accelerate the computation. This approach ensured efficient processing and accurate classification of lung histopathological images.

Experiment and Result

Parameter adjustment incredibly affects the exhibition of the model since they straightforwardly administer the model's training. Also, fine-tuning can avoid overfitting and the structure of a summed-up model. Therefore, in our project, for the correct classification of lung cancer histology images into three classes, more effective CNN pretrained models, EfficientNetB3 and ResNet50, are chosen. Our proposed method for this model consists of two parts.

1. First, we download and import EfficientNetB3 and ResNet50.
2. Fine-tuned, fully connected layers.

In the first step, EfficientNetB3 and ResNet50 are added with setting weight to ImageNet. In the fully connected layer (FCL), “Softmax” is used as an activation function. The reason for using Softmax is that the classification is categorical.

We conducted an extensive experimental analysis using Python programming packages such as Keras and TensorFlow on Kaggle. The experiments were carried out on a computer with the following specifications: an AMD A6 CPU, 8 GB RAM, and virtual P100 GPU that supports parallel computation during training and testing phases. The entire process was implemented on the Windows 10 platform.

4.1 Model Training

Three models were trained for lung cancer detection: a custom CNN model , an EfficientNetB3 and a ResNet50 model fine-tuned for this specific task. The training process included:

- Optimizer: Adamax with a learning rate of 0.001
- Loss Function: Categorical Cross-Entropy
- Epochs: 20

4.2 Performance Metrics

The performance of the models was evaluated using the following metrics:

- Accuracy: Accuracy is the ratio of correctly predicted instances to the total instances.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- Precision: Precision is the ratio of correctly predicted positive observations to the total predicted positives.

$$Precision = \frac{TP}{TP + FP}$$

- Recall: Recall (or Sensitivity) is the ratio of correctly predicted positive observations to all the observations in the actual class.

$$Recall = \frac{TP}{TP + FN}$$

- F1-Score: F1-Score is the harmonic mean of precision and recall, providing a balance between the two metrics.

$$F1.Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Where TP, FP, FN, and TN represent the output measures as true positive, false positive, false negative, and true negative values for the training and validation images of the models.

4.3 Proposed CNN model performance

The images were trained for 20 epochs with batch size 32 with 375 steps in each epoch.

	precision	recall	f1-score	support
Lung_squamous_cell_carcinoma	0.98	1.00	0.99	493
Lung_adenocarcinoma	1.00	0.98	0.99	515
Lung_benign_tissue	1.00	1.00	1.00	492
accuracy			0.99	1500
macro avg	0.99	0.99	0.99	1500
weighted avg	0.99	0.99	0.99	1500

Figure 4.1-Measure the performance of our CNN model

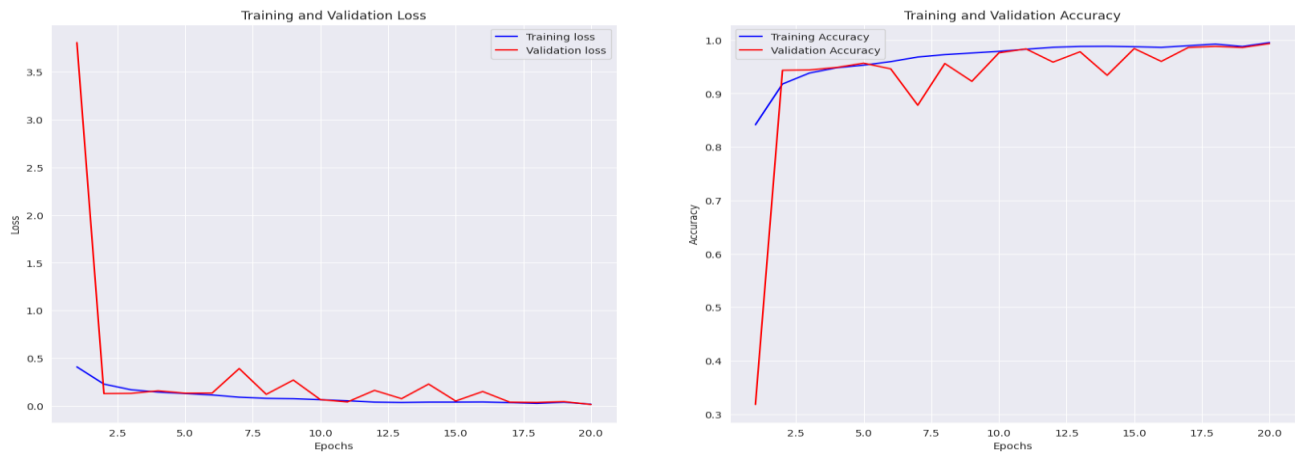


Figure 4.2-Our CNN model training and validation plot of accuracy and loss.

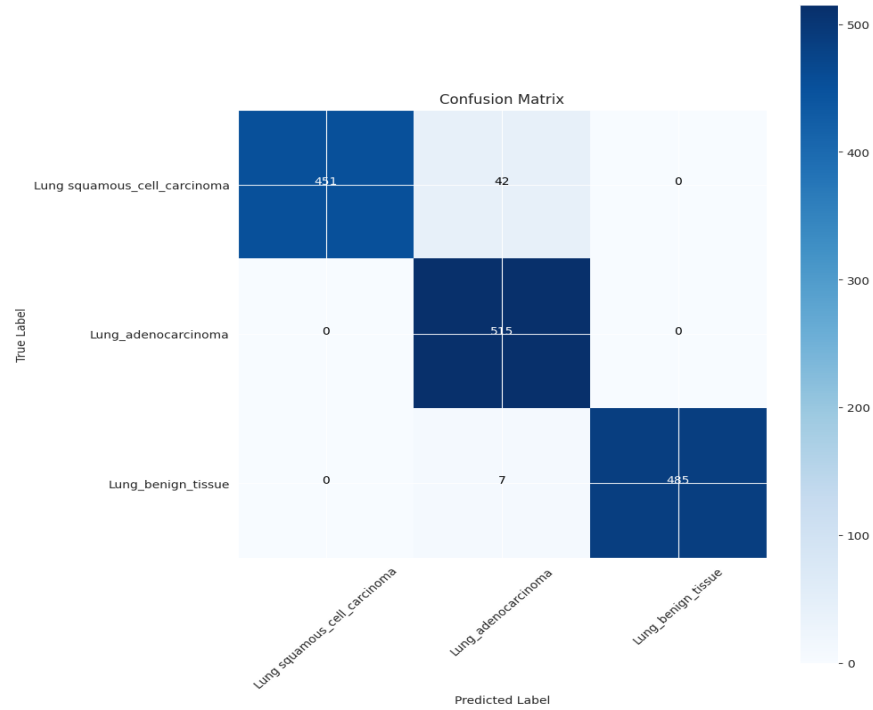


Figure 4.3-Confusion Matrix of our CNN Different Image Categories for Validation Images

4.4 Fine-tuned ResNet50 model performance

After evaluating the Fine Tuned Resnet50 model was able to achieve a training accuracy of 100% and a validation accuracy of 99.86% in the final epoch. Below images shows the plot of model accuracy vs. epoch and model loss vs. epoch for training and validation images.

	precision	recall	f1-score	support
Lung squamous_cell_carcinoma	0.99	1.00	0.99	493
Lung_adenocarcinoma	1.00	0.99	0.99	515
Lung_benign_tissue	1.00	1.00	1.00	492
accuracy			0.99	1500
macro avg	0.99	0.99	0.99	1500
weighted avg	0.99	0.99	0.99	1500

Figure 4.4-Measure the performance of our ResNet50 model

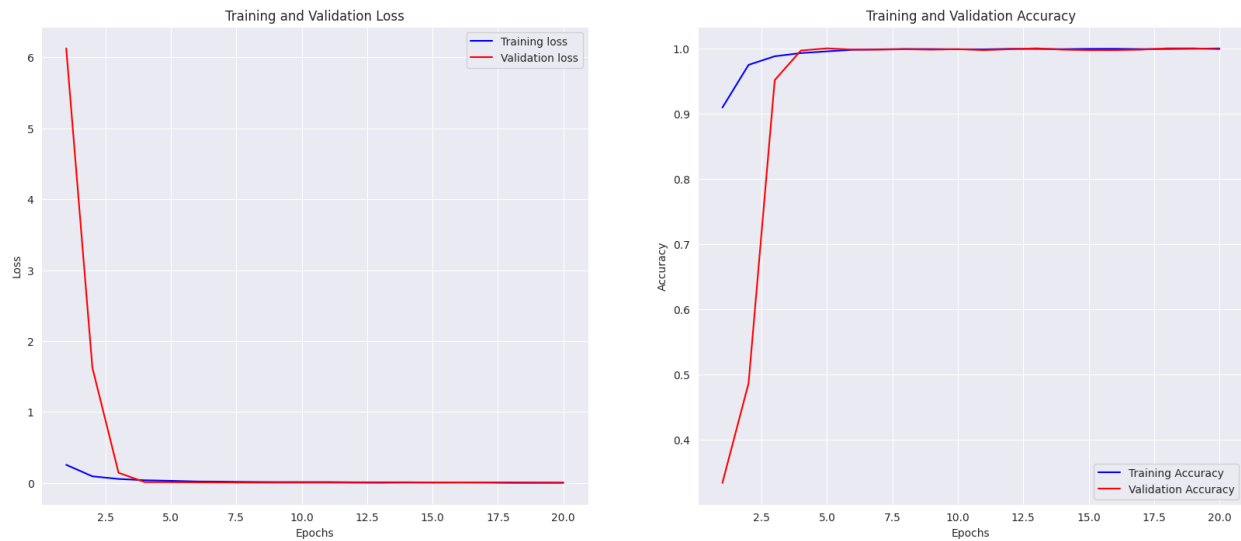


Figure 4.5-Resnet50 model training and validation plot of accuracy and loss.

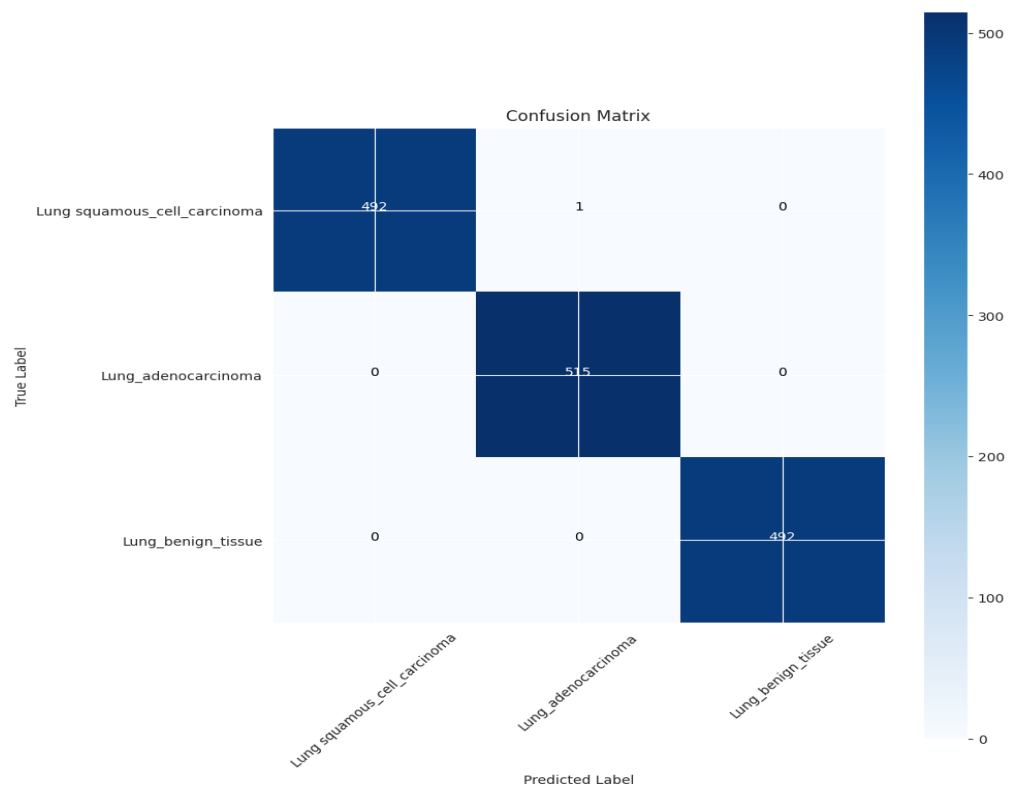


Figure 4.6- Confusion Matrix of ResNet50 model of Different Image Categories for Validation Images

4.5 Fine-tuned EfficientNetB3 model performance

After evaluating the Fine Tuned EfficientNetB3 model was able to achieve a training results for EfficientNetB3 are 100% accuracy and 0.00068 loss and having 224×224 image resolution.

	precision	recall	f1-score	support
Lung_squamous_cell_carcinoma	1.00	1.00	1.00	493
Lung_adenocarcinoma	1.00	1.00	1.00	515
Lung_benign_tissue	1.00	1.00	1.00	492
accuracy			1.00	1500
macro avg	1.00	1.00	1.00	1500
weighted avg	1.00	1.00	1.00	1500

Figure 4.7-Measure the performance of our EfficientNetB3 model

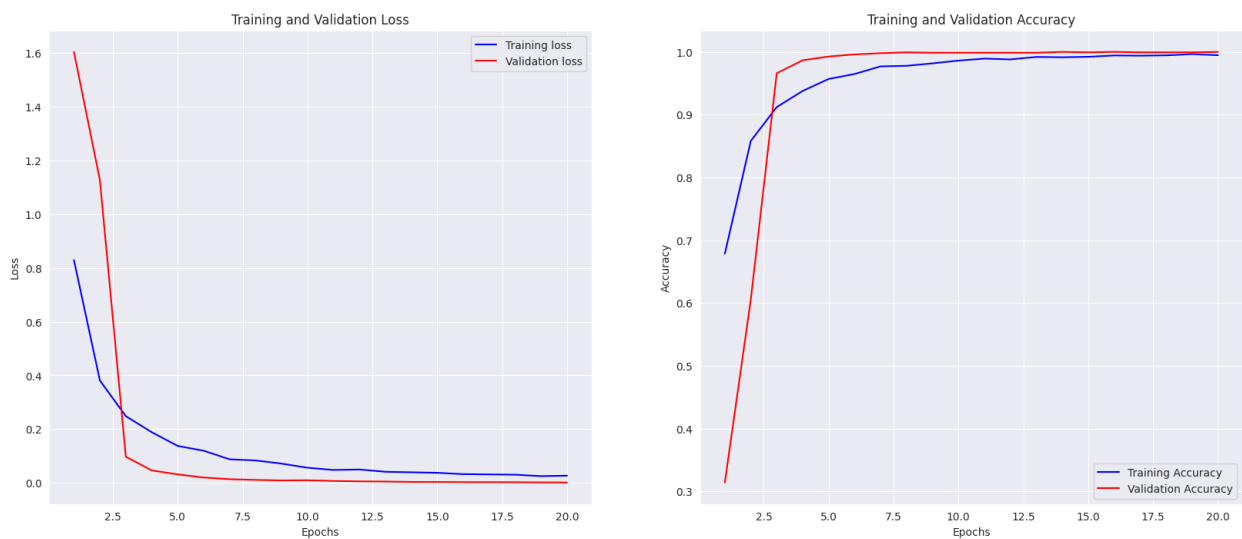


Figure 4.8-EfficientNetB3 model training and validation plot of accuracy and loss

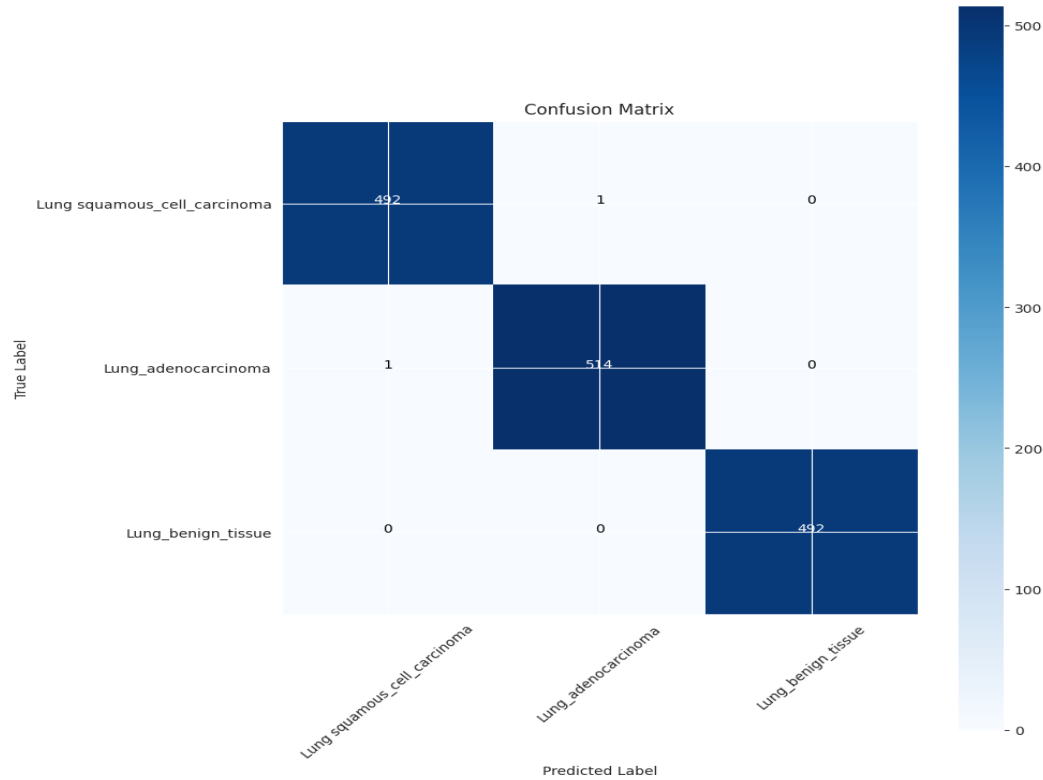


Figure 4.9-Confusion Matrix of EfficientNetB3 model of Different Image Categories for Validation Images

4.6 Model Comparison

The influence of transfer learning has been examined through fine-tuned models. The earlier ImageNet dataset had previously pre-trained those models. This chosen collection fine-tuned the final few convolutions along with all of the FC layers over transfer learning, whereas the dataset provided by ImageNet optimized filter weights within the early convolutional layer training. In terms of precision, F1 score, accuracy, and Recall, a comparison of all models are summarized in the table below:

Model	Accuracy	F1-Score	Precision	Recall
Our model	0.97	0.97	0.97	0.97
ResNet50	0.99	0.98	0.99	0.99
EfficientNetB3	1.0	0.99	0.98	0.98

Table 4.1 – Model comparison summary

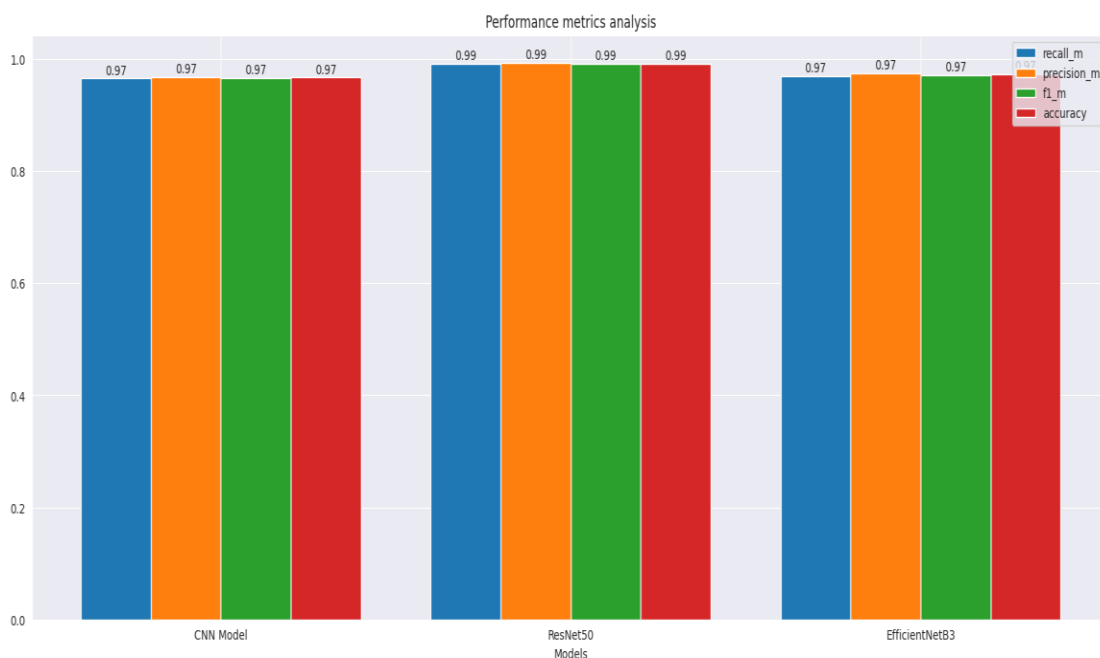


Figure 4.9

4.7 Analysis

The ResNet50 model outperformed the custom CNN model and EfficientNetB3 in all evaluated metrics, achieving the highest accuracy, precision, recall, and F1-score. The EfficientNetB3 model showed competitive results, surpassing the custom CNN model in precision and recall, but it did not reach the performance levels of the ResNet50 model.

The proposed ResNet50 model demonstrated exceptional performance in lung cancer detection, indicating its suitability for this critical task.

The use of transfer learning with the ResNet50 model, which leverages pre-trained weights from large-scale image datasets, significantly contributed to its superior performance.

Conclusion and Future work

This research work presents lung cancer detection using histopathological images. A convolutional neural network (CNN) was implemented to classify an image of three different categories benign, Adenocarcinoma, and squamous cell carcinoma. The model was able to achieve 99% and 98.20% of training and validation accuracy. The precision, f1- score, recall were calculated, and a confusion matrix plot was drawn to measure the model performance.

We utilized a robust methodology, beginning with the collection and preprocessing of a comprehensive dataset of lung histopathological images. Our model architecture was carefully designed to include multiple convolutional and dense layers, enabling the extraction of relevant features and improving the overall classification performance. Specifically, we compared the performance of our CNN model, ResNet50, and EfficientNetB3, using key metrics such as accuracy, precision, recall, and F1-Score.

The experimental results demonstrated that our ResNet50 model achieved superior performance across all metrics, indicating its effectiveness in accurately detecting lung cancer. The comparison of models, as visualized in the performance metrics analysis chart, highlighted the significant improvements made by our proposed approach.

Our findings suggest that the use of advanced CNN architectures, particularly ResNet50, can substantially improve the accuracy of lung cancer detection from histopathological images. This has the potential to aid medical professionals in early diagnosis and treatment, ultimately contributing to better patient outcomes.

Future work could explore the integration of additional imaging modalities and the application of more sophisticated data augmentation techniques to further enhance model robustness and generalization. Additionally, deploying the model in a real-world clinical setting would provide valuable insights into its practical applicability and performance.

Overall, this project underscores the promising potential of deep learning techniques in medical image analysis and their critical role in advancing healthcare technologies.

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