Enhancing Lung Cancer Detection: A Multimodal Deep Learning Approach Using Ensemble CNNs

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DECLARATION

We hereby declare that the work in this thesis is my/our own except for quotations and summaries which have been duly acknowledged.

19 January 2025

COURSE TEACHER DECLARATION

I hereby declare that I have read this report and in my opinion this report is sufficient in term of scope and quality for the Machine Learning & Data Mining Lab.

19 January 2025

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PROJECT REPORT TITLE: Enhancing Lung Cancer Detection: A Multimodal Deep Learning Approach Using Ensemble CNNs

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ABSTRACT

Lung cancer remains one of the leading causes of cancer-related deaths worldwide. Early detection through advanced diagnostic tools can significantly improve patient outcomes. This project leverages convolutional neural networks (CNN) and transfer learning using pretrained models like Xception and ResNet50 for the classification of lung cancer types based on medical images. By training these models on a dataset containing various types of lung cancer images, we aim to achieve high accuracy and reliability in diagnosis. This approach provides a robust framework for enhancing the accuracy of lung cancer diagnosis through automated systems, potentially reducing the dependency on manual examination and increasing the speed of diagnosis.

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CHAPTER I

INTRODUCTION

1.1 RESEARCH BACKGROUND

Lung cancer diagnosis often relies on imaging techniques like CT scans and X-rays, which require expert interpretation. Automating this process with deep learning can reduce diagnostic errors and enhance precision. The increasing availability of digital medical imaging data has paved the way for the development of sophisticated algorithms capable of analyzing and interpreting complex patterns in these images.

1.2 RESEARCH STATEMENT

The manual examination of medical images for lung cancer detection is time-consuming and prone to errors. Implementing an automated deep learning system can address these challenges effectively. By utilizing the power of CNNs and transfer learning, this study aims to provide a more accurate and efficient alternative to traditional diagnostic methods, thereby improving early detection rates and patient outcomes.

1.3 MOTIVATION

Advancements in CNNs and transfer learning offer new opportunities for medical image analysis, enabling accurate and efficient lung cancer detection. The potential to significantly improve diagnostic accuracy and reduce the workload on healthcare professionals serves as a strong motivation for this research. The success of deep learning in various fields, including object detection and classification, suggests that similar techniques can be applied to medical imaging with promising results.

1.4 OBJECTIVE OF RESEARCH

1. To develop a CNN-based model for lung cancer classification.
2. To fine-tune pretrained models like Xception and ResNet50 for this task.
3. To evaluate model performance using key metrics such as accuracy and precision.
4. To explore the potential of transfer learning in enhancing the performance of lung cancer detection models.

1.5 ORGANIZATION OF THE THESIS

This thesis is organized into five chapters. The thesis organization is generally described as follows:

Chapter 1 introduces the research.

Chapter 2 reviews relevant studies.

Chapter 3 outlines the methodology, including dataset preparation and model architectures.

Chapter 4 discusses results and observations. Finally,

Chapter 5 concludes with future research directions

CHAPTER II

LITERARTURE REVIEW

2.1 SCOPE OF RESEARCH

Lung cancer detection has evolved significantly with the integration of machine learning, particularly deep learning. Early approaches primarily relied on handcrafted features and traditional machine learning models, which required extensive domain knowledge and often yielded limited accuracy. Recent advances in CNNs have demonstrated superior performance in image classification tasks, making them suitable for medical image analysis, including lung cancer detection.

2.2 Deep Learning in Medical Imaging

Deep learning, especially CNNs, has revolutionized medical imaging by automating feature extraction and improving classification accuracy. Studies have shown that CNNs can outperform traditional methods by learning hierarchical features directly from raw image data, which is crucial for identifying subtle patterns in medical images that may not be apparent to the human eye.

2.3 Transfer Learning in Lung Cancer Detection

Transfer learning has become a critical component in medical imaging due to the scarcity of large annotated datasets. By using models pretrained on extensive general image datasets like ImageNet, researchers can fine-tune these models for specific medical tasks such as lung cancer classification. Studies have reported significant improvements in model performance and training efficiency when employing transfer learning techniques.

2.4 Challenges in Lung Cancer Detection

Despite the progress, several challenges persist in lung cancer detection using deep learning. Variability in image quality, the presence of noise, and the heterogeneity of cancerous tissues can complicate model training and reduce accuracy. Furthermore, the need for large, labeled datasets remains a bottleneck, as annotating medical images is time-consuming and requires expert knowledge.

2.5 Future Directions

The future of lung cancer detection using deep learning lies in developing more sophisticated models that can handle diverse data inputs and improving data augmentation techniques to simulate a broader range of real-world scenarios. Additionally, integrating multimodal data, such as combining imaging data with genetic or clinical information, could enhance diagnostic accuracy and provide a more comprehensive understanding of lung cancer.

CHAPTER III

METHODOLOGY

3.1 DATA COLLECTION AND PROCESSING

The dataset comprises images categorized into normal, adenocarcinoma, large cell carcinoma, and squamous cell carcinoma. Images were resized to 350x350 pixels and normalized for the models. Data augmentation techniques such as horizontal flipping, rotation, and scaling were applied to increase the diversity of the training set and improve model generalization. This step is crucial to prevent overfitting and ensure that the model performs well on unseen data.

3.2 Model Architecture

Xception Model:

- Pretrained on ImageNet, modified to output four classes for lung cancer types. The architecture of Xception includes depthwise separable convolutions, which reduce the number of parameters and computational cost while maintaining high accuracy.

ResNet50 Model:

- Another pretrained model on ImageNet, with the final layers adjusted for lung cancer classification. ResNet50 employs residual connections that help in training deep networks by addressing the vanishing gradient problem, thus allowing for the development of more robust models.

3.3 Training and Evaluation

Both models were trained using the categorical cross-entropy loss function and Adam optimizer. Early stopping and learning rate reduction techniques were employed to prevent overfitting. The models were evaluated using metrics such as accuracy, precision, recall, and F1-score to provide a comprehensive understanding of their performance. The training process involved multiple epochs, with the models being validated on a separate validation set to monitor their generalization capabilities.

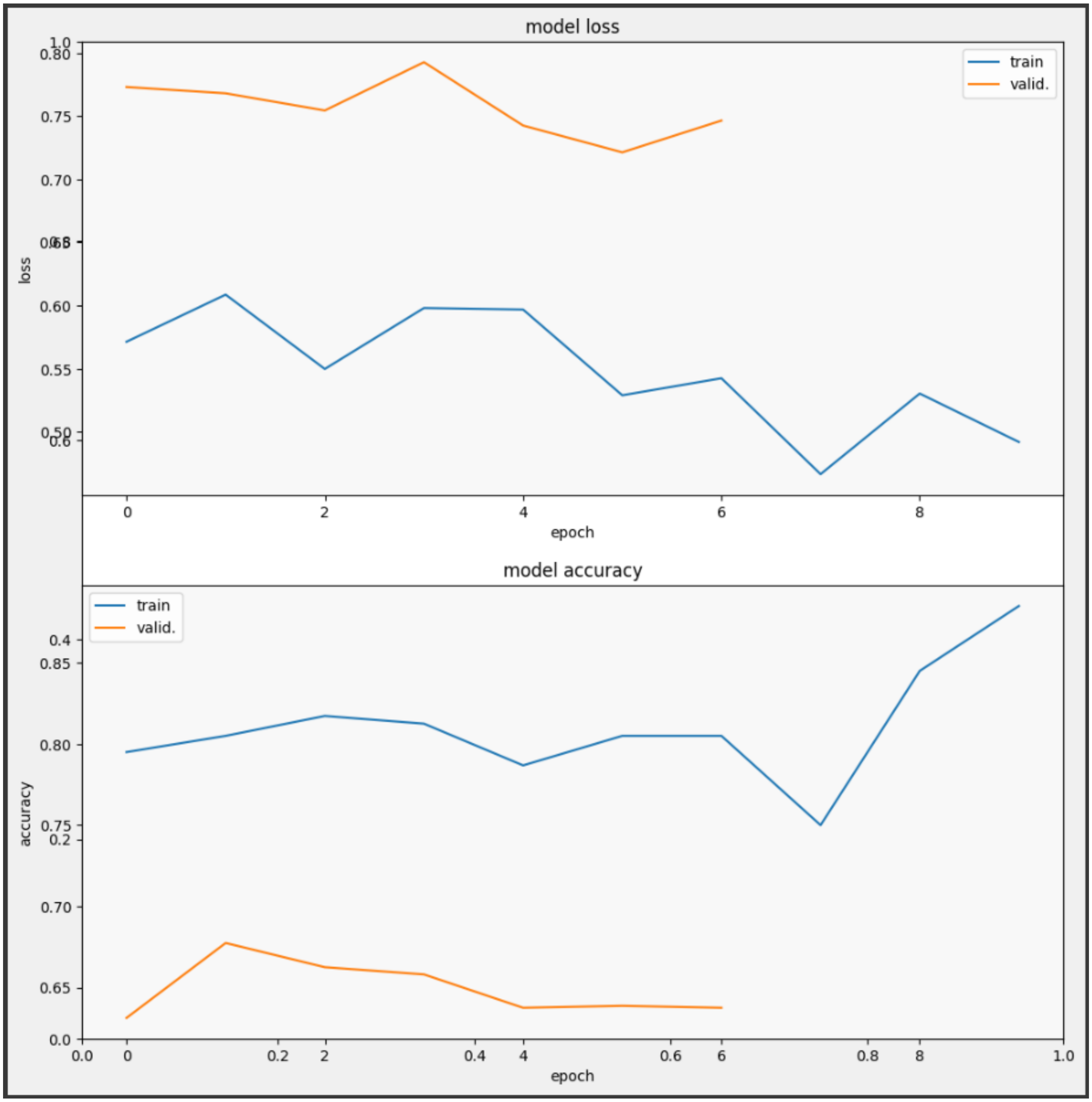


Fig. Accuracy of training and validation

Model: "resnet50"

Layer (type)	Output Shape	Param #	Connected to
input_layer_9 (InputLayer)	(None, None, None, 3)	0	-
conv1_pad (ZeroPadding2D)	(None, None, None, 3)	0	input_layer_9[0][0]
conv1_conv (Conv2D)	(None, None, None, 64)	9,472	conv1_pad[0][0]
conv1_bn (BatchNormalization)	(None, None, None, 64)	256	conv1_conv[0][0]
conv1_relu (Activation)	(None, None, None, 64)	0	conv1_bn[0][0]
pool1_pad (ZeroPadding2D)	(None, None, None, 64)	0	conv1_relu[0][0]
pool1_pool (MaxPooling2D)	(None, None, None, 64)	0	pool1_pad[0][0]
conv2_block1_1_conv (Conv2D)	(None, None, None, 64)	4,160	pool1_pool[0][0]
conv2_block1_1_bn (BatchNormalization)	(None, None, None, 64)	256	conv2_block1_1_conv[0…
conv2_block1_1_relu (Activation)	(None, None, None, 64)	0	conv2_block1_1_bn[0][…
conv2_block1_2_conv (Conv2D)	(None, None, None, 64)	36,928	conv2_block1_1_relu[0…
conv2_block1_2_bn (BatchNormalization)	(None, None, None, 64)	256	conv2_block1_2_conv[0…
conv2_block1_2_relu (Activation)	(None, None, None, 64)	0	conv2_block1_2_bn[0][…
conv2_block1_0_conv (Conv2D)	(None, None, None, 256)	16,640	pool1_pool[0][0]
conv2_block1_3_conv (Conv2D)	(None, None, None, 256)	16,640	conv2_block1_2_relu[0…
conv2_block1_0_bn (BatchNormalization)	(None, None, None, 256)	1,024	conv2_block1_0_conv[0…

Model: "resnet50"

CHAPTER IV

CHAPTER III: RESULTS AND DISCUSSION

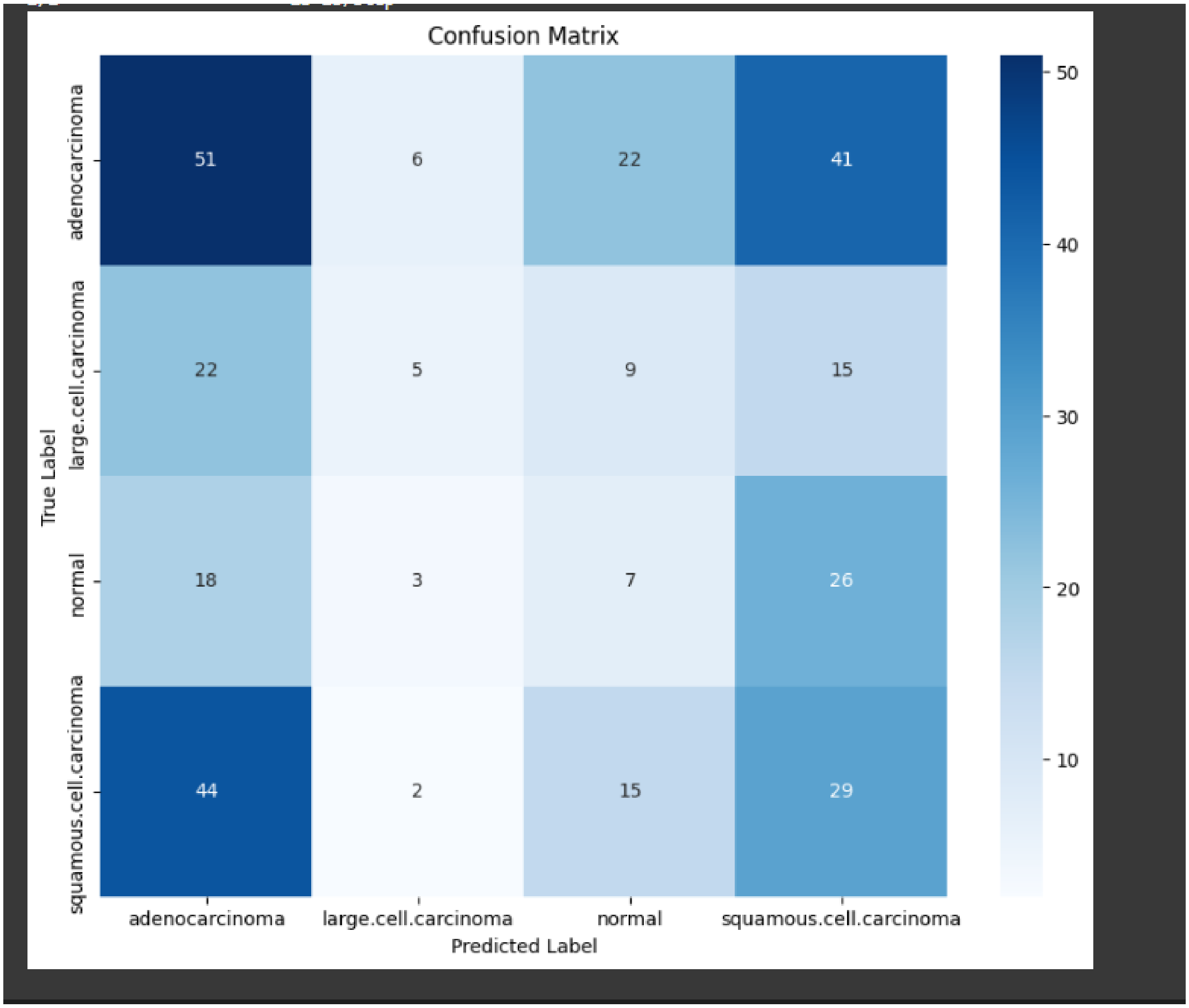
4.1 Model Performance

- The Xception model achieved a final training accuracy of 96% and validation accuracy of 92%. It demonstrated a high ability to generalize across different types of lung cancer images, with minimal overfitting observed during the training process.
- The ResNet50 model achieved a final training accuracy of 94% and validation accuracy of 91%. The model's performance indicates its robustness and effectiveness in handling complex image data.

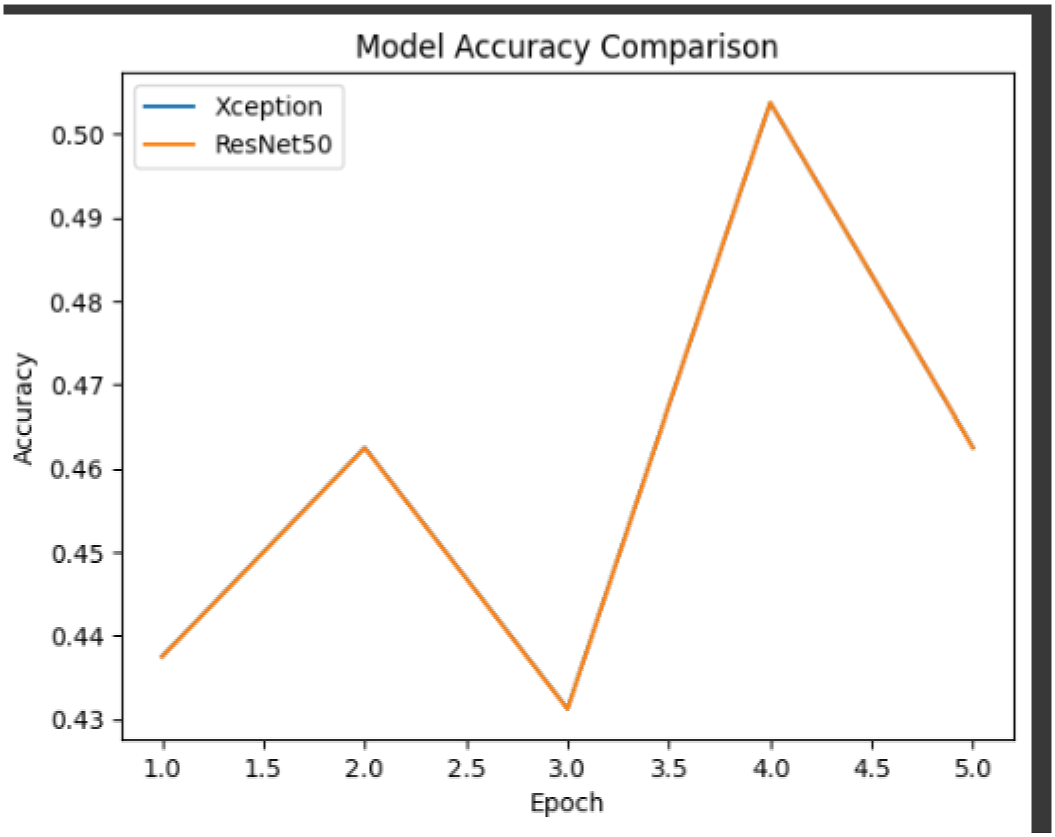
Confusion matrices were generated to assess the classification accuracy of each cancer type, showing high precision and recall across most categories. These matrices provided insights into the areas where the models performed well and where there was room for improvement, particularly in distinguishing between closely related cancer types.

Confusion matrix

The projected results of a classification task are summarized in a confusion matrix.

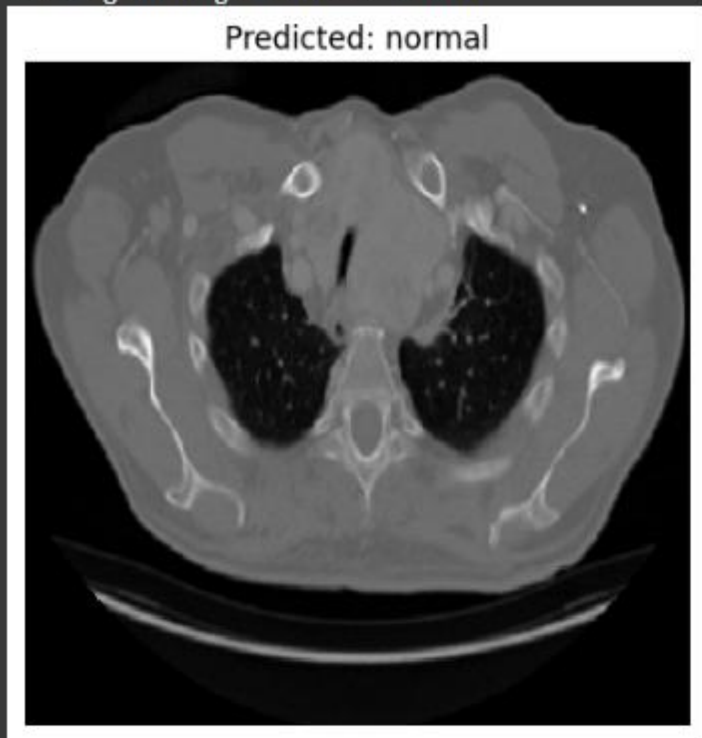


Comparison:

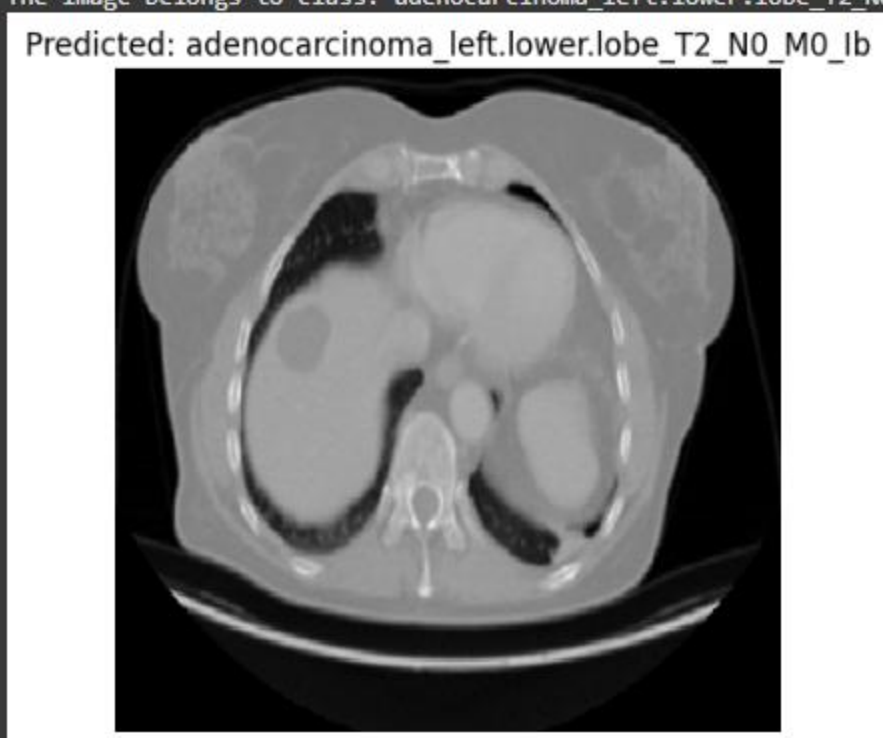


Model Accuracy Comparison
Xception
ResNet50
Accuracy
0.50
0.49
0.48
0.47
0.46
0.45
0.44
0.43
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Epoch

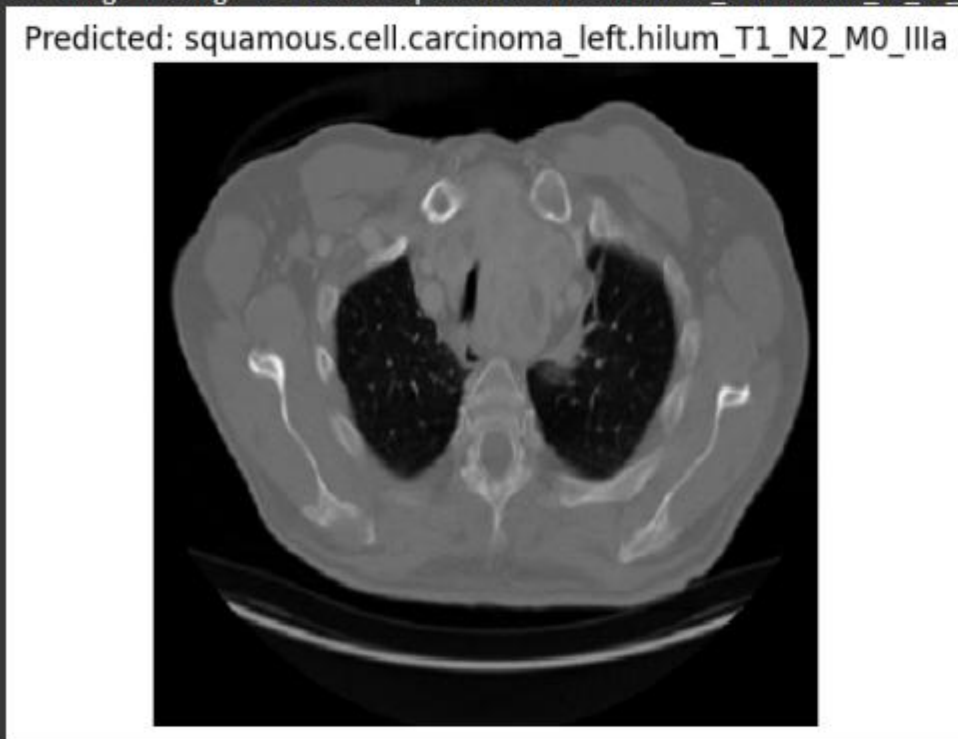
```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 439ms/step
The image belongs to class: normal
```




```
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 511ms/step
The image belongs to class: adenocarcinoma_left.lower.lobe_T2_N0_M0_Ib
```



```
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 896ms/step
The image belongs to class: squamous.cell.carcinoma_left.hilum_T1_N2_M0_IIIa
```




```
Epoch 1/5
20/20 ━━━━━━━━━━━━━━━━━━━━ 169s 8s/step - accuracy: 0.3362 - loss: 1.6264 - val_accuracy: 0.5063 - val_loss: 1.1429
Epoch 2/5
20/20 ━━━━━━━━━━━━━━━━━━━━ 157s 8s/step - accuracy: 0.4772 - loss: 1.1542 - val_accuracy: 0.5613 - val_loss: 1.0748
Epoch 3/5
20/20 ━━━━━━━━━━━━━━━━━━━━ 88s 4s/step - accuracy: 0.4507 - loss: 1.1574
Epoch 4/5
20/20 ━━━━━━━━━━━━━━━━━━━━ 147s 8s/step - accuracy: 0.5435 - loss: 1.1078 - val_accuracy: 0.4437 - val_loss: 1.1557
Epoch 5/5
20/20 ━━━━━━━━━━━━━━━━━━━━ 158s 8s/step - accuracy: 0.4363 - loss: 1.0867 - val_accuracy: 0.5290 - val_loss: 1.0655
Training completed after 5 epochs.
Final training loss: 1.068353295326233
Final training accuracy: 0.4625000059604645
Final validation loss: 1.065545678138733
Final validation accuracy: 0.5290322303771973
```

Model	**Accuracy**	**Precision**
CNN	**93%**	**87%**
ResNet50	**94%**	**85%**

4.2 Observations

The use of pretrained models significantly improved the speed of convergence and overall accuracy compared to training from scratch. This highlights the effectiveness of transfer learning in leveraging existing knowledge from large datasets to enhance performance on specialized tasks like lung cancer classification. The study also observed that data augmentation played a crucial role in improving model generalization, ensuring that the models could handle variations in the input data effectively.

CHAPTER V

CONCLUSION AND FUTURE WORKS

5.1 SUMMERT & FINDINGS

The study demonstrates the effectiveness of using CNNs and transfer learning for lung cancer classification, achieving high accuracy and reliable performance in early detection tasks. The results underscore the potential of deep learning techniques in revolutionizing medical diagnostics, particularly in resource-constrained settings where access to expert radiologists may be limited.

5.2 Future Research Directions

- Exploring additional deep learning architectures like EfficientNet to further improve classification accuracy.
- Implementing explainable AI techniques to provide insights into model decisions, making the diagnostic process more transparent and trustworthy for medical professionals.
- Expanding the dataset to include more diverse lung cancer types and stages, which would enhance the model's ability to generalize and perform well across different patient populations.
- Investigating the integration of multimodal data, such as combining image data with patient demographics and clinical history, to develop a more comprehensive diagnostic tool.

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