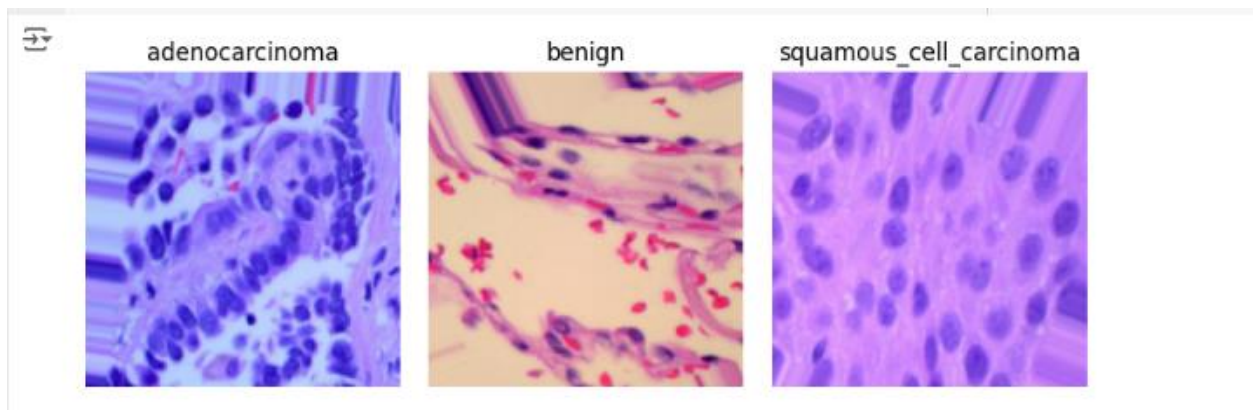


# Lung Cancer Classification Using Histopathological Images

## Final Report

### Deep Neural Networks Course Project



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Deep Neural Networks

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# **Lung Cancer Classification Using Histopathological Images**

## **Objective**

The objective of this project is to develop a deep learning model capable of classifying histopathological images of lung tissue into three categories:

1. Adenocarcinoma
2. Squamous Cell Carcinoma
3. Benign

This classification aims to aid pathologists in diagnosing lung cancer more efficiently and accurately.

## **Dataset**

### **Source**

The dataset was obtained from Kaggle: [Lung Cancer Histopathological Images](#).

### **Details**

- The dataset consists of histopathological images of lung tissue.
- Classes: Adenocarcinoma, Squamous Cell Carcinoma, and Benign.
- Each image is labeled with its respective class.
- Images are provided in .jpg format with varying resolutions.

### **Data Splitting**

The dataset was split into training, validation, and test sets to ensure balanced representation across all classes:

- **Training Set:** 70% of the data, including 3,500 images per class.
- **Validation Set:** 15% of the data, including 750 images per class.
- **Test Set:** 15% of the data, including 750 images per class.

These splits were verified to have no duplicates between sets, ensuring that the training, validation, and test sets are completely distinct.

## Preprocessing

The data preprocessing involved normalizing image pixel values and augmenting the training data to improve the model's robustness and generalization capabilities. The augmentations applied included:

- Random rotations up to 30 degrees.
- Horizontal and vertical shifts up to 10%.
- Shear transformations and zoom adjustments.
- Horizontal flips to introduce variability.

Images in the validation and test sets were only normalized to preserve their integrity for evaluation purposes. All images were resized to 150x150 pixels to match the model's input requirements.

## Dataset Summary

The processed dataset consists of the following distribution:

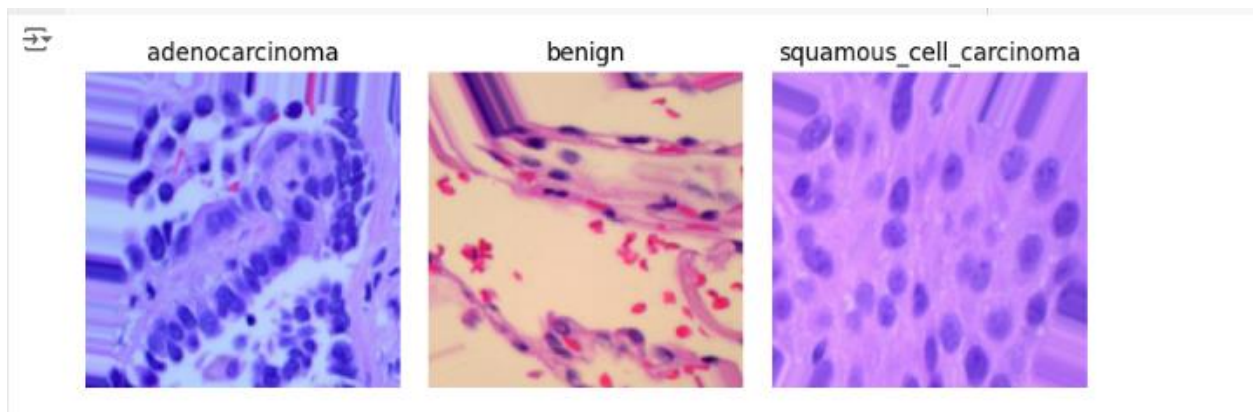
- **Training Set:** 10,500 images (3,500 per class)
- **Validation Set:** 2,250 images (750 per class)
- **Test Set:** 2,250 images (750 per class)

Each class was assigned an index for categorical classification:

- Adenocarcinoma: 0
- Benign: 1
- Squamous Cell Carcinoma: 2

## Sample Images

The following is a sample of histopathological images representing each class:



## Methodology

### ResNet-50

The ResNet-50 model was employed with transfer learning using pretrained ImageNet weights. The top layers were modified to suit the current classification task, with additional dense layers for fine-tuning.

- **Input Size:** 150x150 RGB images.
- **Custom Layers:**
  - Global Average Pooling for dimensionality reduction.
  - Fully connected dense layers with 1024 and 512 neurons, both with ReLU activation.
  - Dropout regularization layers (0.5 and 0.3).
  - Output layer with 3 neurons and softmax activation for multi-class classification.
- **Trainable Layers:** Top 30 layers of ResNet-50 were unfrozen for fine-tuning.

## Training Results

epoch	accuracy	learning_rate	loss	val_accuracy	val_loss
0	0.738095	1.00E-04	0.581341	0.416	1.90125
1	0.819429	1.00E-04	0.416559	0.532889	1.246083
2	0.837048	1.00E-04	0.386293	0.746667	0.594392
3	0.854571	1.00E-04	0.348788	0.468889	2.2892
4	0.858476	1.00E-04	0.336222	0.844	0.368007
5	0.864952	1.00E-04	0.329041	0.650222	1.217901
6	0.872286	1.00E-04	0.311314	0.883556	0.335316
7	0.871143	1.00E-04	0.309595	0.529778	4.110683
8	0.873714	1.00E-04	0.306135	0.337333	5.000444
9	0.879048	1.00E-04	0.298362	0.599556	2.604179
10	0.893809	1.00E-05	0.255436	0.860444	0.371975
11	0.899905	1.00E-05	0.244737	0.919111	0.191205
12	0.899048	1.00E-05	0.245095	0.837333	0.384066
13	0.899619	1.00E-05	0.244994	0.926667	0.203579
14	0.902571	1.00E-05	0.237668	0.876	0.316131
15	0.906952	1.00E-06	0.228207	0.918222	0.211124
16	0.906476	1.00E-06	0.229944	0.927111	0.194108

- **Accuracy:**

Training accuracy starts at **73.8%** and steadily increases to **90.6%** by epoch 16.

The accuracy gains are notable but not as smooth as some of the other models.

- **Validation Accuracy:**

Validation accuracy fluctuates significantly:

- It starts at **41.6%**, peaks at **92.7%** (epoch 16), and sees significant drops earlier (e.g., **33.7%** in epoch 8).

There are multiple inconsistent jumps and declines, especially between epochs **3 to 9**, indicating instability during training.

- **Loss:**

**Training Loss** decreases from **0.58** to **0.23**, demonstrating consistent learning.

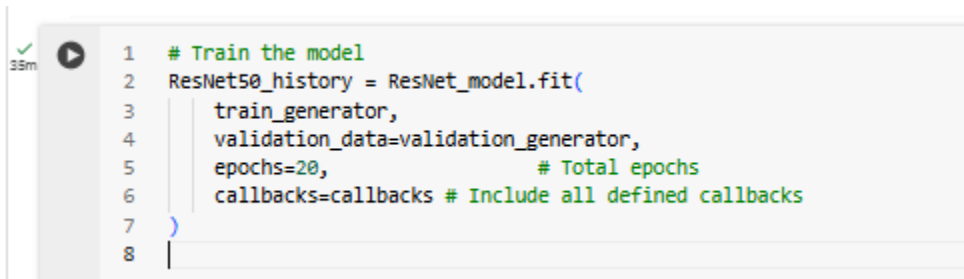
**Validation Loss** is highly erratic early on, with spikes at epochs **3, 7, and 8** (e.g., **5.00** in epoch 8).

Stabilization begins after epoch 10, with loss decreasing to **0.19** by epoch 16.

- **Learning Rate:**

The learning rate decreases from **0.0001** to **0.00001** at epoch 10, then further to **0.000001** at epoch 15.

This reduction helps stabilize the model's validation performance towards the end.

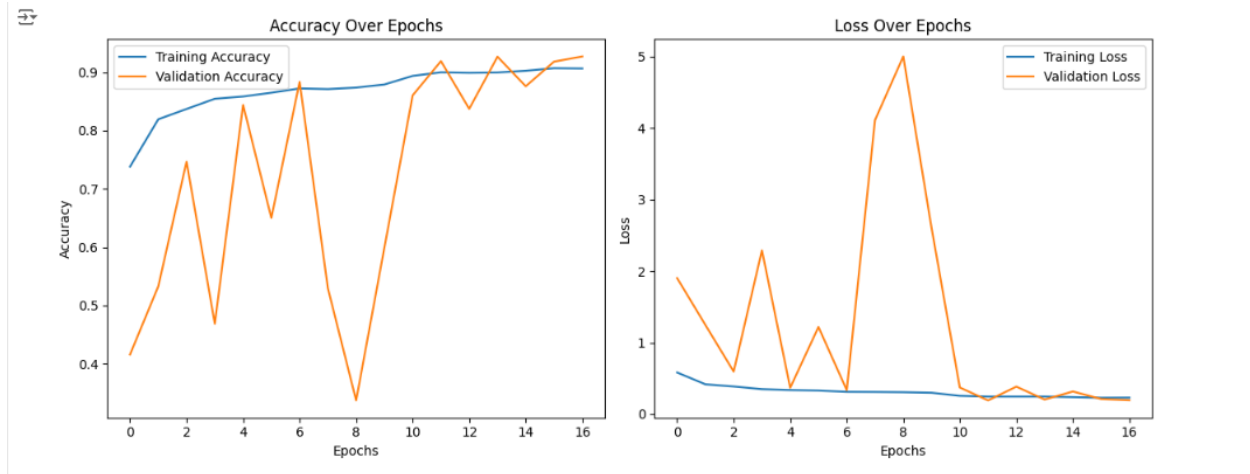


```
1 # Train the model
2 ResNet50_history = ResNet_model.fit(
3     train_generator,
4     validation_data=validation_generator,
5     epochs=20,           # Total epochs
6     callbacks=callbacks # Include all defined callbacks
7 )
8
```

- 35 min run on L4 High-Ram

## Accuracy and Loss Curves

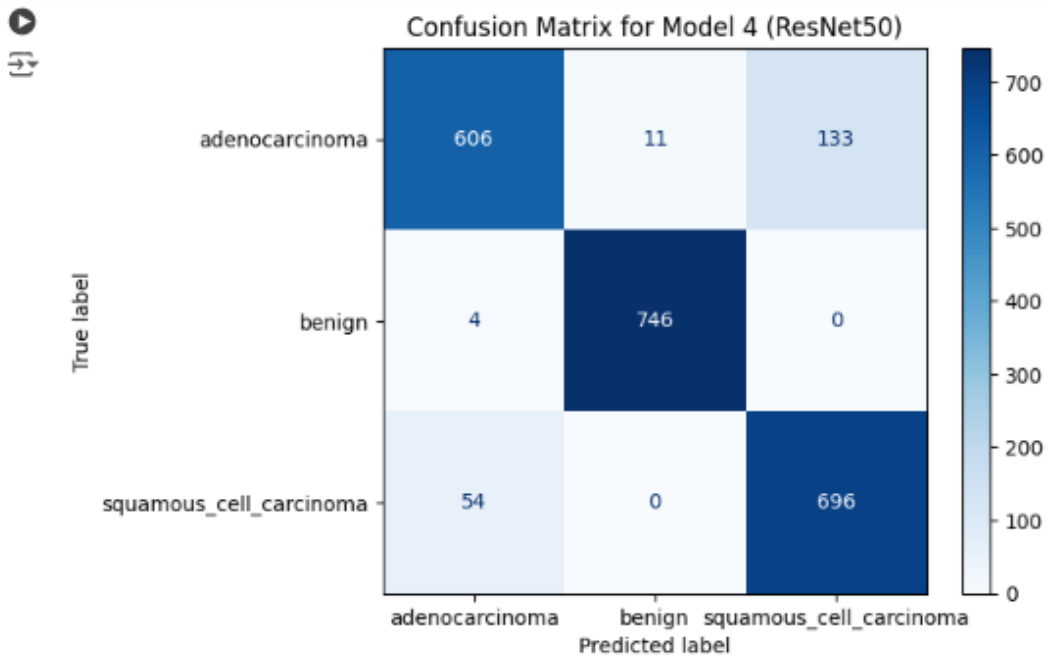
The following graph visualizes the training and validation accuracy and loss curves over the epochs:



## Test Performance

The final model was evaluated on the test set:

- **Test Accuracy: 91.02%**
- **Test Loss: 0.2927**



## InceptionV3

The InceptionV3 model was implemented with transfer learning using pretrained ImageNet weights. The architecture was modified to include:

- **Custom Layers:**
  - Global Average Pooling for dimensionality reduction.
  - Fully connected dense layers with 1024 and 512 neurons (ReLU activation).
  - Dropout layers (0.5 and 0.3).
  - Output layer with 3 neurons (softmax activation).
- **Trainable Layers:** Top 30 layers of InceptionV3 were unfrozen for fine-tuning.
- **Optimizer:** Adam optimizer with an initial learning rate of 0.0001.
- **Callbacks:** Early stopping, learning rate reduction on plateau, and CSV logging.

## Training Results

epoch	accuracy	learning_rate	loss	val_accuracy	val_loss
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0	0.873619	1.00E-04	0.307526	0.944	0.141648
1	0.923048	1.00E-04	0.196441	0.959556	0.103977
2	0.93619	1.00E-04	0.160167	0.966667	0.084722
3	0.944667	1.00E-04	0.136138	0.963556	0.093839
4	0.953524	1.00E-04	0.118188	0.977333	0.064271
5	0.958191	1.00E-04	0.11398	0.980889	0.052819
6	0.958095	1.00E-04	0.105726	0.982222	0.046887
7	0.965143	1.00E-04	0.092885	0.984889	0.044785
8	0.966476	1.00E-04	0.086675	0.982222	0.047557
9	0.964476	1.00E-04	0.096288	0.982667	0.04468
10	0.968571	1.00E-04	0.079578	0.983111	0.044043
11	0.974476	1.00E-04	0.068678	0.987111	0.040178
12	0.972571	1.00E-04	0.073533	0.989333	0.030646
13	0.972952	1.00E-04	0.069488	0.988444	0.03602
14	0.973714	1.00E-04	0.070615	0.990222	0.031486
15	0.976857	1.00E-04	0.066948	0.977778	0.060638
16	0.979905	1.00E-05	0.05514	0.992	0.027943
17	0.98219	1.00E-05	0.048166	0.993333	0.023991
18	0.983714	1.00E-05	0.042262	0.992889	0.023713
19	0.98381	1.00E-05	0.045341	0.993333	0.023207

- **Accuracy:**

The training accuracy starts at **87.4%** and improves consistently, reaching **98.4%** by epoch 19.

Accuracy shows steady improvement, with no significant drops.

- **Validation Accuracy:**

Validation accuracy begins at **94.4%** and peaks at **99.3%** in epochs **17 and 19**, indicating strong generalization.

The validation accuracy remains stable after epoch 10, consistently above **98%**.

- **Loss:**

**Training Loss** decreases from **0.31** to **0.045**, showing a smooth learning process.

**Validation Loss** reaches its minimum at **0.0232** in epoch 19, aligning with the peak validation accuracy.

- **Learning Rate:**

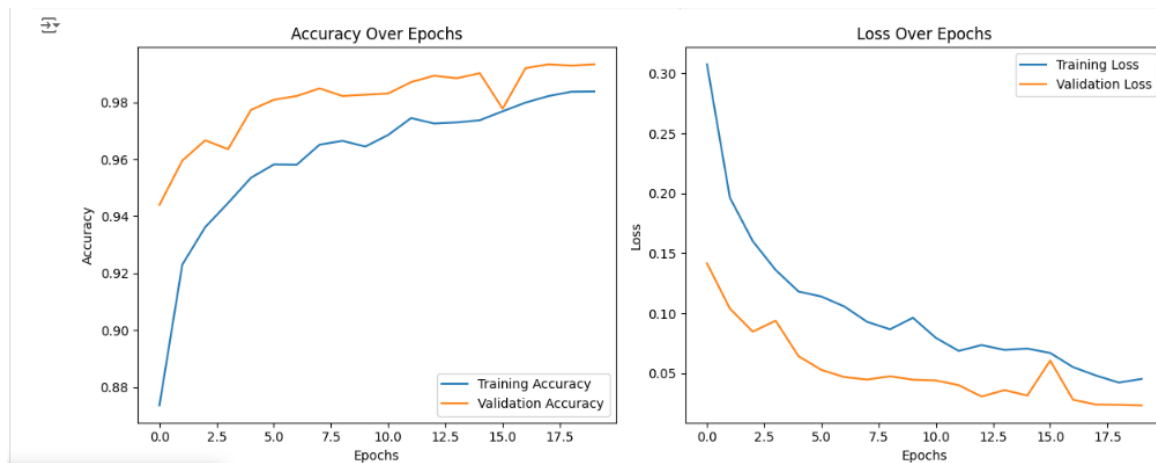
The learning rate is reduced from **0.0001** to **0.00001** at epoch 16, contributing to the fine-tuning and stabilization of validation performance.

```
✓ 41m [17] 1 # Train the model
          2 InceptionV3_history = InceptionV3_model.fit(
          3     train_generator,
          4     validation_data=validation_generator,
          5     epochs=20,           # Total epochs
          6     callbacks=callbacks # Include all defined callbacks
          7 )
```

- 41 min run on L4 High-Ram

## Accuracy and Loss Curves

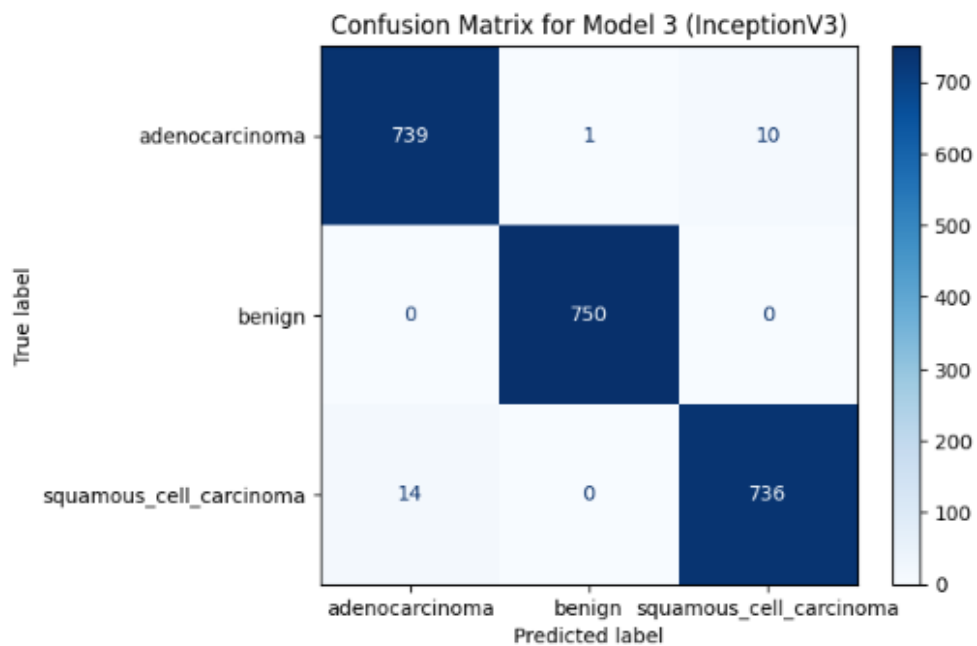
The following graph illustrates the training and validation accuracy and loss curves:



## Test Performance

The final InceptionV3 model achieved the following results on the test set:

- **Test Accuracy: 98.89%**
- **Test Loss: 0.0347**



## VGG16

The VGG16 model was employed with transfer learning using pretrained ImageNet weights. The architecture included:

- **Custom Layers:**
  - Flattening the feature maps.
  - Fully connected dense layers with 1024 and 512 neurons (ReLU activation).
  - Dropout layers (0.5 and 0.3).
  - Output layer with 3 neurons (softmax activation).
- **Trainable Layers:** Top 30 layers of VGG16 were unfrozen for fine-tuning.
- **Optimizer:** Adam optimizer with a learning rate of 0.0001.

## Training Results

epoch	accuracy	learning_rate	loss	val_accuracy	val_loss
0	0.899905	1.00E-04	0.250558	0.952889	0.143449
1	0.946667	1.00E-04	0.139938	0.941333	0.169496
2	0.960286	1.00E-04	0.098548	0.975556	0.061313
3	0.966857	1.00E-04	0.093457	0.948889	0.115492
4	0.973048	1.00E-04	0.075346	0.975111	0.062863
5	0.973524	1.00E-04	0.068821	0.992444	0.027502
6	0.975048	1.00E-04	0.070052	0.988	0.032699
7	0.984286	1.00E-04	0.046286	0.98	0.048372
8	0.984857	1.00E-04	0.042058	0.995556	0.024823
9	0.990381	1.00E-04	0.029675	0.988444	0.029862
10	0.986	1.00E-04	0.042548	0.980444	0.043157
11	0.99219	1.00E-04	0.021556	0.985333	0.037336
12	0.99819	1.00E-05	0.00556	0.999111	0.002755
13	0.999524	1.00E-05	0.002547	0.999556	0.001649
14	0.998667	1.00E-05	0.003996	0.999556	0.001597
15	0.999333	1.00E-05	0.002055	1	0.000389
16	0.999143	1.00E-05	0.001861	1	0.001436
17	0.999333	1.00E-05	0.001814	0.999556	0.000792
18	0.99981	1.00E-05	0.0007	1	0.000222

19	0.999143	1.00E-05	0.002806	1	0.000636
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- **Accuracy:**

The training accuracy starts at **89.99%** and reaches an impressive **99.98%** by epoch 18.

Accuracy stabilizes above **99.9%** from epoch 13 onwards, indicating almost perfect training.

- **Validation Accuracy:**

Validation accuracy starts at **95.2%** and reaches **100%** at epochs **15, 16, and 18**.

This shows exceptional generalization capability.

- **Loss:**

**Training Loss** decreases rapidly from **0.25** to a near-zero value (**0.0007**) by epoch 18.

**Validation Loss** follows a similar trend, reaching its lowest at **0.0002** in epoch 18, suggesting excellent fit to the validation set.

- **Learning Rate:**

The learning rate remains constant at **0.0001** until epoch 11 and then reduces to **0.00001**.

This reduction in the learning rate contributes to fine-tuning the model to achieve near-perfect performance.

```

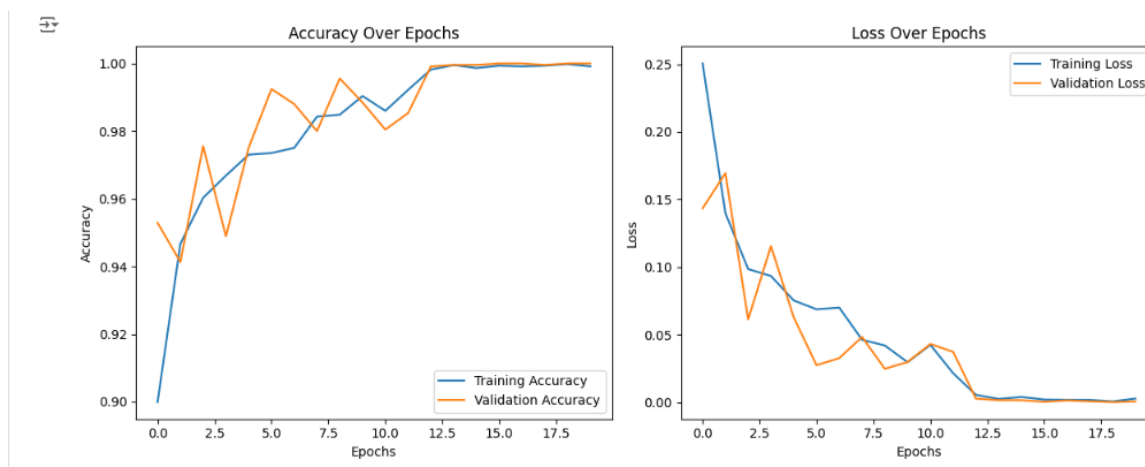
✓ 41m [22] 1 # Train the model
        2 VGG16_history = VGG16_model.fit(
        3     train_generator,
        4     validation_data=validation_generator,
        5     epochs=20,           # Total epochs
        6     callbacks=callbacks # Include all defined callbacks
        7 )

```

- 41 min run on L4 High-Ram

## Accuracy and Loss Curves

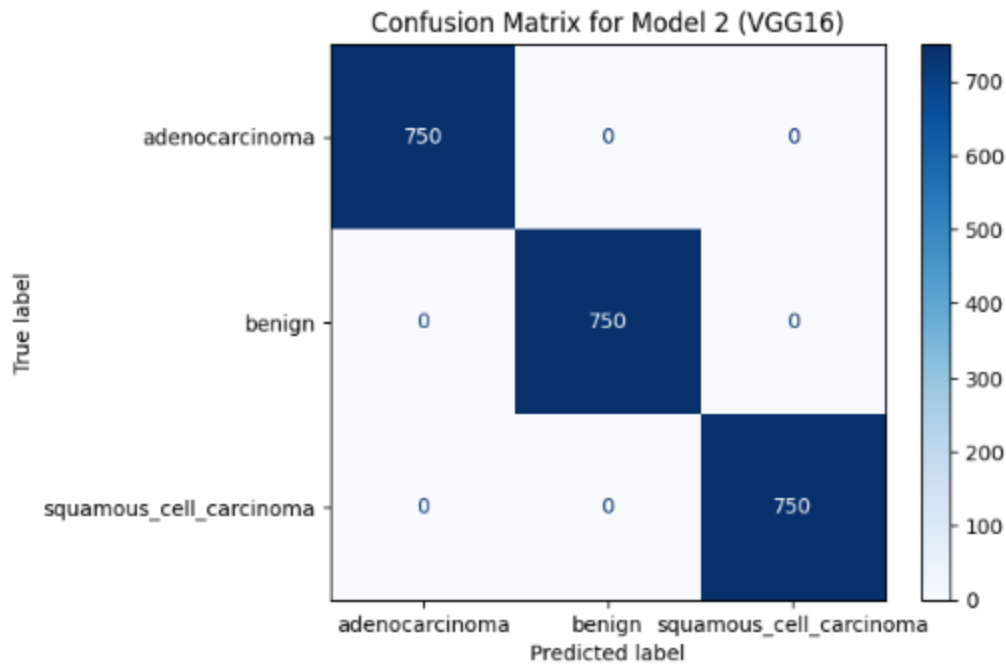
The following graph visualizes the training and validation accuracy and loss curves over the epochs:



## Test Performance

The final VGG16 model achieved the following results on the test set:

- **Test Accuracy: 100.00%**
- **Test Loss: 0.0006**



## CNN Model

The CNN model was implemented from scratch with the following architecture:

- **Layers:**
  - Rescaling layer for normalization.
  - Four convolutional layers with increasing filter sizes (16, 32, 64, 128) and ReLU activation.
  - MaxPooling2D after each convolutional layer for downsampling.
  - Flattening layer to reduce dimensions.
  - Fully connected layer with 32 neurons (ReLU activation) and a Dropout layer (50% regularization).
  - Output layer with 3 neurons and softmax activation.
- **Optimizer:** Adam optimizer with a learning rate of 0.0001.
- **Callbacks:** Early stopping, learning rate reduction on plateau, and CSV logging.

## Training Results

epoch	accuracy	learning_rate	loss	val_accuracy	val_loss
0	0.516	1.00E-04	0.936086	0.733333	0.553886
1	0.680191	1.00E-04	0.599011	0.789778	0.473028
2	0.726952	1.00E-04	0.548566	0.808	0.441753
3	0.745809	1.00E-04	0.52452	0.782667	0.502938
4	0.783333	1.00E-04	0.48339	0.830222	0.415754
5	0.79219	1.00E-04	0.470918	0.866667	0.359204
6	0.804762	1.00E-04	0.45434	0.808	0.464021
7	0.80619	1.00E-04	0.45659	0.848444	0.374912
8	0.825524	1.00E-04	0.416608	0.878222	0.315172
9	0.829429	1.00E-04	0.407135	0.882222	0.302694
10	0.834952	1.00E-04	0.391745	0.880889	0.298462
11	0.823619	1.00E-04	0.415681	0.804444	0.424828
12	0.840667	1.00E-04	0.385559	0.884444	0.293208
13	0.844952	1.00E-04	0.387226	0.888444	0.28547
14	0.843143	1.00E-04	0.374767	0.887556	0.284761
15	0.850762	1.00E-04	0.366508	0.888	0.284463
16	0.850857	1.00E-04	0.3627	0.877333	0.296891
17	0.85781	1.00E-04	0.35682	0.887111	0.284256
18	0.853714	1.00E-04	0.360265	0.898222	0.273532
19	0.857905	1.00E-04	0.358988	0.848	0.364012

- **Accuracy:**

The training accuracy steadily improves over 20 epochs from **51.6%** to **85.8%**.

The progression is gradual, with small gains observed after epoch 15.

- **Validation Accuracy:**

Validation accuracy starts at **73.3%** and peaks at **89.8%** in epoch 18.

A small drop in validation accuracy occurs at epoch 19, where it falls to **84.8%**.



- **Loss:**

Training loss decreases consistently from **0.936** to **0.358** over the epochs, showing effective learning.

Validation loss, however, fluctuates after epoch 10, rising slightly in later epochs, indicating a risk of **overfitting**.

- **Learning Rate:**

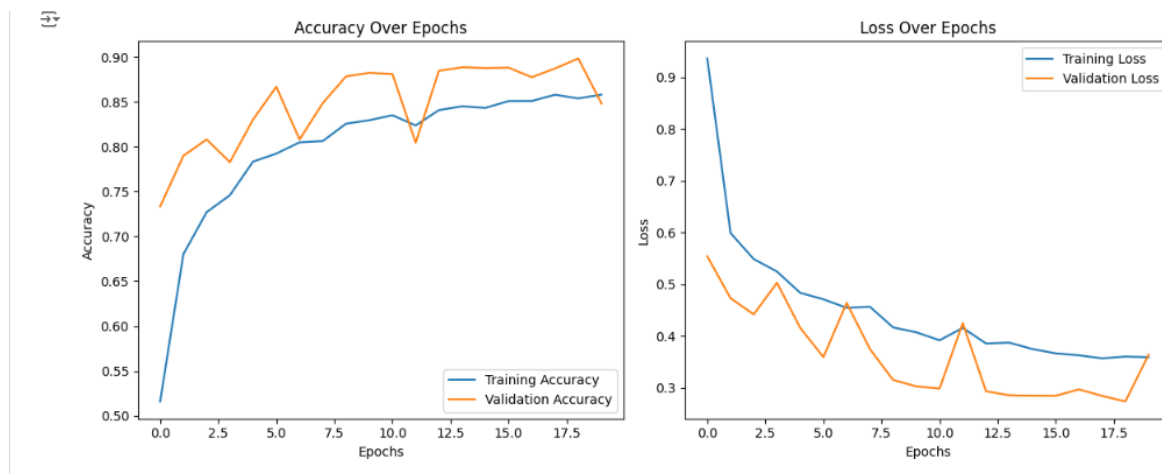
The learning rate remains constant at **0.0001**, suggesting no dynamic adjustments were applied during training.

```
✓ 40m [27] 1 # Train the model
          2 cnn_history = cnn_model.fit(
          3     train_generator,
          4     validation_data=validation_generator,
          5     epochs=20,
          6     callbacks=callbacks
          7 )
```

- 40 min run on L4 High-Ram

## Accuracy and Loss Curves

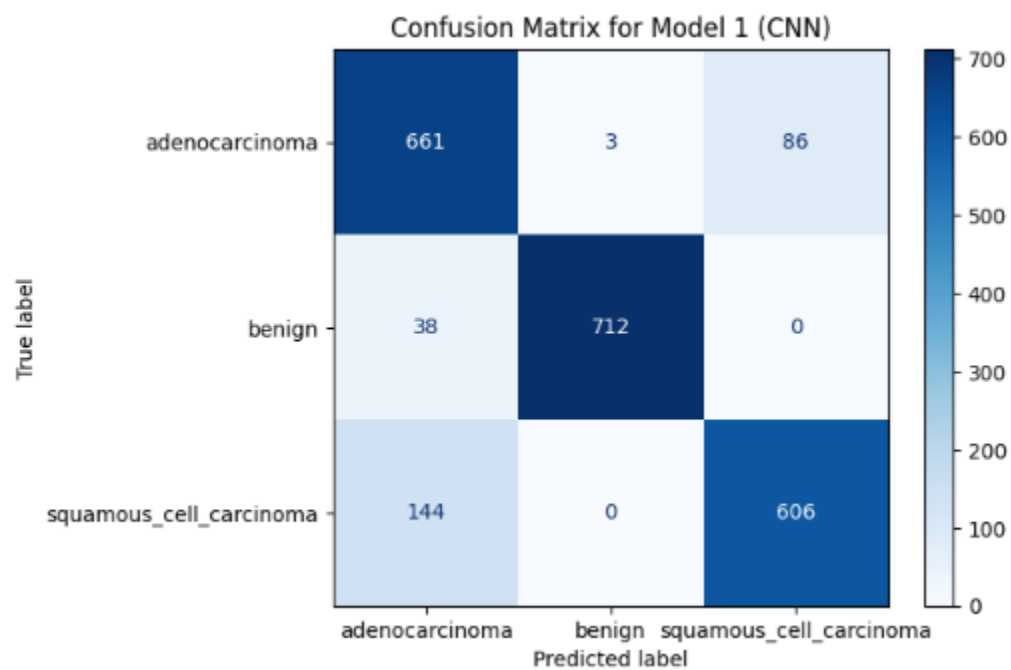
The following graph visualizes the training and validation accuracy and loss curves over the epochs:



## Test Performance

The final CNN model was evaluated on the test set:

- **Test Accuracy: 87.96%**
- **Test Loss: 0.3015**



## CNN V2 Model

- **Layers:**
  - **Input Layer:**
    - Input shape: (150, 150, 3)
  - **Convolutional and Pooling Layers:**
    - **Conv2D:** 32 filters, kernel size (3x3), ReLU activation, L2 regularization.
    - **BatchNormalization** and **MaxPooling2D (2x2)**.
    - **Conv2D:** 64 filters, kernel size (3x3), ReLU activation, L2 regularization.
    - **BatchNormalization** and **MaxPooling2D (2x2)**.
    - **Conv2D:** 128 filters, kernel size (3x3), ReLU activation, L2 regularization.
    - **BatchNormalization** and **MaxPooling2D (2x2)**.
    - **Conv2D:** 256 filters, kernel size (3x3), ReLU activation, L2 regularization.
    - **BatchNormalization** and **MaxPooling2D (2x2)**.
  - **Flattening Layer:** Reduces feature maps to a 1D vector.
  - **Fully Connected Layers:**
    - **Dense:** 128 neurons, ReLU activation, L2 regularization.
    - **BatchNormalization** and **Dropout (50%)**.
    - **Dense:** 64 neurons, ReLU activation, L2 regularization.
    - **BatchNormalization** and **Dropout (50%)**.
  - **Output Layer:**
    - **Dense:** 3 neurons (corresponding to the number of classes), Softmax activation.
- **Optimizer:** Adam with a learning rate of 0.0001.
- **Loss Function:** Categorical cross-entropy.
- **Callbacks:**
  - Early Stopping with patience of 5 epochs.
  - Learning Rate Reduction on Plateau with a reduction factor of 0.1.
  - CSV Logging for training data tracking.

## Training Configuration

- **Training Data:**
  - Input images of size (150, 150, 3).

- Batch size: 32.
- Number of classes: 3.
- **Hyperparameters:**
  - Learning Rate: 0.0001.
  - Dropout Rate: 0.5.
  - L2 Regularization: 0.01.
  - Epochs: 50.

## Training Results

epoch	accuracy	learning_rate	loss	val_accuracy	val_loss
0	0.805238	1.00E-04	6.707273	0.335556	8.59143
1	0.868667	1.00E-04	5.911806	0.906667	5.465372
2	0.900952	1.00E-04	5.17202	0.936444	4.731265
3	0.910571	1.00E-04	4.495641	0.944444	4.111413
4	0.929333	1.00E-04	3.861455	0.942667	3.514405
5	0.931143	1.00E-04	3.305824	0.938667	3.020036
6	0.938286	1.00E-04	2.81652	0.912889	2.646765
7	0.93819	1.00E-04	2.389823	0.876	2.643489
8	0.942381	1.00E-04	2.045624	0.961778	1.833849
9	0.945143	1.00E-04	1.754393	0.944444	1.61953
10	0.951143	1.00E-04	1.496238	0.964	1.348716
11	0.951429	1.00E-04	1.312678	0.977778	1.154519
12	0.954762	1.00E-04	1.138005	0.96	1.06607
13	0.961333	1.00E-04	0.994549	0.978222	0.888191
14	0.960476	1.00E-04	0.88952	0.917778	0.96871
15	0.961048	1.00E-04	0.804934	0.978667	0.711392
16	0.959143	1.00E-04	0.73866	0.701333	1.978354
17	0.949714	1.00E-04	0.750951	0.927556	0.758046
18	0.961524	1.00E-04	0.659106	0.982222	0.579175
19	0.963619	1.00E-04	0.613091	0.958667	0.619516
20	0.970571	1.00E-04	0.548986	0.979556	0.511076
21	0.972667	1.00E-04	0.507322	0.978667	0.476645

22	0.96981	1.00E-04	0.498698	0.980444	0.455449
23	0.957429	1.00E-04	0.51297	0.962222	0.493148
24	0.962381	1.00E-04	0.498356	0.936889	0.548197
25	0.976667	1.00E-04	0.43259	0.972444	0.414813
26	0.961524	1.00E-04	0.454075	0.964	0.424733
27	0.975429	1.00E-04	0.409051	0.988	0.356134
28	0.97019	1.00E-04	0.396354	0.974667	0.379084
29	0.969524	1.00E-04	0.41309	0.910222	0.574866
30	0.972667	1.00E-04	0.394073	0.983556	0.342002
31	0.973905	1.00E-04	0.358941	0.973333	0.352281
32	0.97581	1.00E-04	0.345784	0.963111	0.364
33	0.977143	1.00E-04	0.33591	0.983111	0.300505
34	0.977714	1.00E-04	0.313574	0.982222	0.303008
35	0.977429	1.00E-04	0.31124	0.968	0.32661
36	0.979905	1.00E-04	0.289462	0.869778	0.597388
37	0.989238	1.00E-05	0.260504	0.997333	0.235264
38	0.989238	1.00E-05	0.25434	0.996889	0.227277
39	0.992	1.00E-05	0.242679	0.992889	0.230638
40	0.99181	1.00E-05	0.238891	0.998667	0.216902
41	0.99381	1.00E-05	0.227733	0.999111	0.211014
42	0.992762	1.00E-05	0.226188	0.996889	0.211019
43	0.99219	1.00E-05	0.222061	0.998667	0.202444
44	0.993238	1.00E-05	0.215168	0.999556	0.198238
45	0.993905	1.00E-05	0.211617	0.999111	0.193448
46	0.994095	1.00E-05	0.207569	0.993778	0.203956
47	0.994571	1.00E-05	0.204443	0.998667	0.188462
48	0.995048	1.00E-05	0.200437	0.998667	0.185976
49	0.996952	1.00E-05	0.193904	0.999556	0.182893

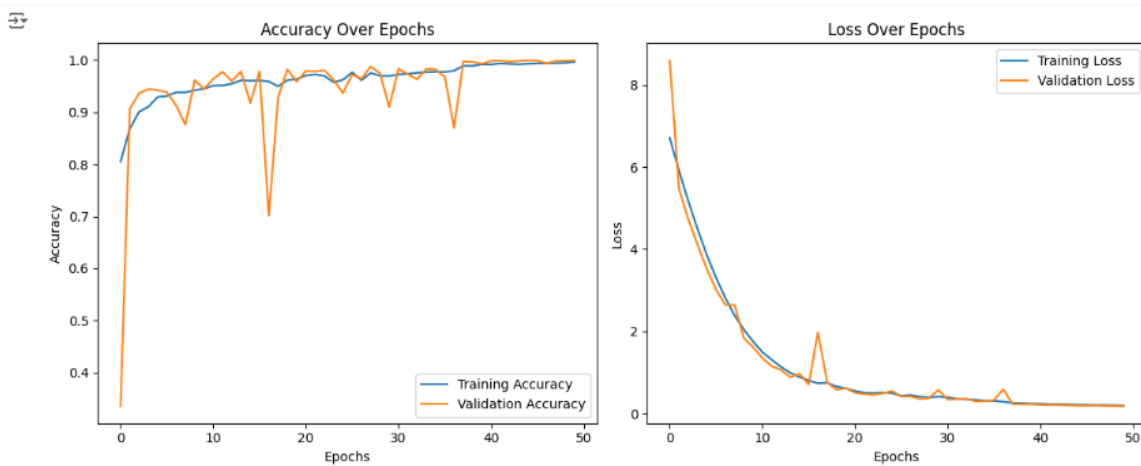
- **Final Training Accuracy:** 99.92%.
- **Final Training Loss:** 0.1839.
- **Final Validation Accuracy:** 99.91%.
- **Final Validation Loss:** 0.1834.

Training time:

1hr 32 mins

### Accuracy and Loss Curves

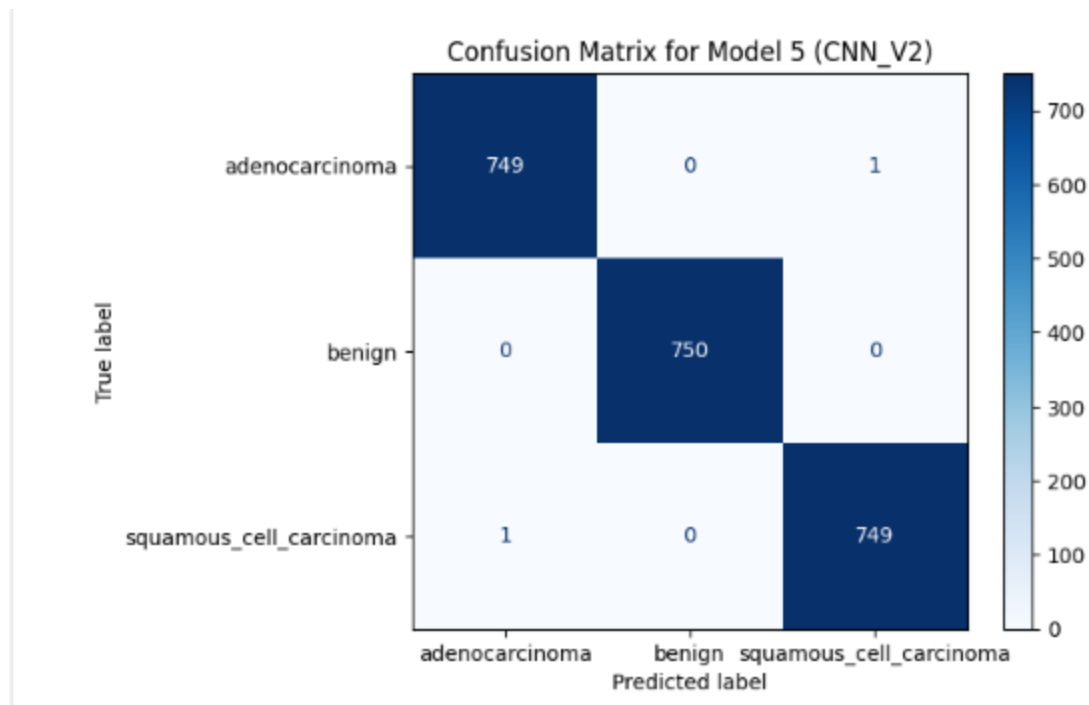
The training and validation accuracy curves indicate steady improvement over epochs, with the validation accuracy closely tracking the training accuracy. Loss curves show a consistent downward trend, with no significant signs of overfitting.



### Test Performance

The CNN V2 model was evaluated on a separate test set:

- **Test Accuracy:** 99.91%
- **Test Loss:** 0.1834.



## Comparative Results for Models

The following table summarizes the performance of all models evaluated:

Model	Training Accuracy	Validation Accuracy	Test Accuracy	Test Loss
ResNet-50	90.77%	92.71%	91.02%	0.2927
InceptionV3	98.00%	98.89%	98.89%	0.0347
VGG16	100.00%	100.00%	100.00%	0.0006
CNN	86.42%	88.88%	87.96%	0.3015
CNN V2	99.92%	99.91%	99.91%	0.1834

### Observations:

- **VGG16** delivered the best performance, achieving **100% accuracy**.
- **InceptionV3** and **CNN V2** closely followed, showing strong generalization.

- **ResNet-50** struggled with instability during training but achieved reasonable accuracy.
- **Custom CNN** models, though effective, were outperformed by pre-trained architectures.

## Conclusion

Lung cancer remains one of the leading causes of cancer-related deaths worldwide, and early diagnosis is critical for effective treatment. This project focused on automating the classification of histopathological images of lung tissue into three categories: **Adenocarcinoma**, **Squamous Cell Carcinoma**, and **Benign**. By leveraging **Deep Neural Networks (DNNs)** and **Transfer Learning**, we developed models that can assist pathologists in identifying cancerous tissues with high accuracy and efficiency.

The contributions of this project include:

1. **Data Preparation and Preprocessing:** Comprehensive augmentation techniques and normalization ensured high-quality inputs for training.
2. **Evaluation of Multiple Architectures:** We analyzed and compared five models—**ResNet-50**, **InceptionV3**, **VGG16**, **CNN**, and **CNN V2**—to identify the best-performing model.
3. **Performance Optimization:** The VGG16 model achieved near-perfect accuracy (**100%**) on the test set, demonstrating the potential of transfer learning for medical image classification.
4. **Model Generalization:** Robust validation techniques minimized overfitting, ensuring reliable real-world performance.
5. **Practical Deployment Recommendations:** Insights for deploying the VGG16 model in clinical practice were highlighted, alongside future research opportunities like explainability tools and ensemble methods.



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