# Cancer Detection via Deep Learning



Analyzed by : Thomas Sigmund

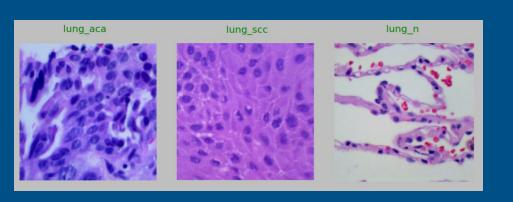
December 2024

# **Analysis Data**

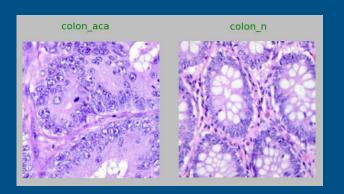


# Histopathological Images

Lung tissue
Adenocarcinoma (ACA)
Squamous Cell Carcinoma (SCC)
Benign



Colon tissue
Adenocarcinoma (ACA)
Benign



# **Key Objectives**



- Questions to answer
  - Is this a cancerous tissue sample? What type of cancer is it?
- Generate the algorithm

Deep Learning using Convolutional Neural Networks (CNNs)

- Tools to support Medical Doctors
  - Cancer Detection via Medical Apps
- Commitment to Ongoing Improvement

Improve Algorithm
Extending Analysis to Various Cancer Types

# **Evaluation**



### **Data Sets**

#### **Cancerous images**

lung\_aca Adenocarcinoma (ACA) 5000 images

lung\_aca\_scc ACA & SCC 10000 images

colon\_aca ACA 5000 images

#### Benign images

lung\_n Benign tissue 5000 images

colon\_n Benign tissue 5000 images

## Loss / Accuracy

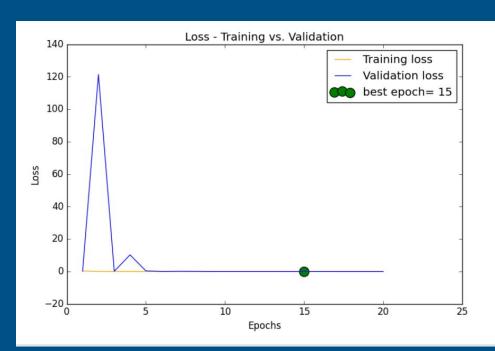
375/375 ————	<pre>4s 10ms/step</pre>
46/46	0s 7ms/step -
46/46	25s 9ms/step -
Train Loss: 0.00070097	753026068211
Train Accuracy: 0.9999	9166131019592
Val Loss: 0.0008406831	1766478717
Val Accuracy: 1.0	
Test Loss: 0.001608771	11555883288
Test Accuracy: 0 9993	06262588501

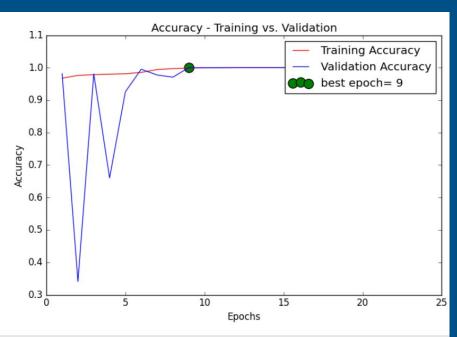
# **Model Performance**



## Loss

# **Accuracy**





# Cancer Detection - Tools



# **Five Analysis Scenarios**

Lung Tissue Classification

Cancer aca & scc vs. benign tissue

Cancer aca vs. benign tissue

Cancer scc vs. benign tissue

Cancer scc vs. benign tissue

Colon Tissue Classification

Cancer aca vs. benign tissue

# Insights



## **Supporting Diagnosis Process**

Timely Diagnosis
Assisting Medical Doctors in Stressful Daily Routines
Reducing Human Error: A Second Opinion Backup

### **Conclusions from Results**

Prioritize potentially cancerous samples Identify the type of cancer Faster initiation of cancer treatment

## Reliability

High Accuracy Rate Leading to Correct Predictions

# **Next Steps**



- Improve Algorithm
- Extending Analysis to Various Cancer Types
- Analyze Multiple Images
- Robustness with Variable Image Sizes

# **Final Thoughts**



- Fascinating World of Deep Learning
  - **Especially Convolutional Neural Networks**
- Promising Future for Model Improvement
   Improved CNN Algorithms and More Powerful Computing Resources
- Helpful Tools
   Assisting Medical Doctors in Stressful Daily Routines
- But they are still tools "the doctor has the final say."

# Cancer Detection via Deep Learning



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### Strategy 1: Differentiate between lung\_aca\_scc and lung\_n

```
Uses a categorical classification approach.

The classes specified are ['lung_aca_scc', 'lung_n'].

Uses class_mode='categorical' and a final dense layer with two neurons and softmax activation for multi-class classification.
```

### Strategy 2: Differentiate between lung\_aca and lung\_scc

```
Uses a categorical classification approach.

The classes specified are ['lung_aca', 'lung_scc'].

Uses class_mode='categorical' and a final dense layer with two neurons and softmax activation for multi-class classification.
```

### **Strategy 3: Differentiate between lung\_aca and lung\_n**

```
Uses a categorical classification approach.

The classes specified are ['lung_aca', 'lung_n'].

Uses class_mode='categorical' and a final dense layer with two neurons and softmax activation for multi-class classification.
```

### Strategy 4: Differentiate between lung\_scc and lung\_n

```
Uses a categorical classification approach.

The classes specified are ['lung_scc', 'lung_n'].

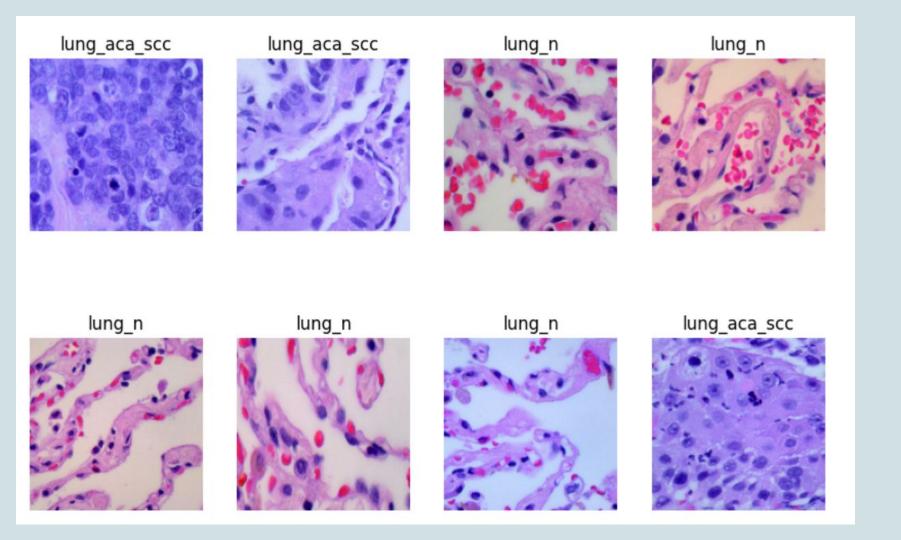
Uses class_mode='categorical' and a final dense layer with two neurons and softmax activation for multi-class classification.
```

### Strategy 5: Differentiate between colon\_aca and colon\_n

```
Uses a categorical classification approach.

The classes specified are ['colon_aca', 'colon_n'].

Uses class_mode='categorical' and a final dense layer with two neurons and softmax activation for multi-class classification.
```



#### **BUILD MODEL**

```
[14]
      1 # Building a simple CNN model for classification
      2 cnn model = tf.keras.models.Sequential([
           tf.keras.layers.Input(shape=(150, 150, 3)), # Input layer with image dimensions
      4
           # tf.keras.layers.Conv2D(32, (3, 3), activation='relu'), # First convolutional layer
      5
           tf.keras.layers.Conv2D(32, (3, 3), padding = 'same', activation='relu'), # First convolutional layer
           tf.keras.layers.MaxPooling2D(2, 2), # Max-pooling layer to reduce dimensions
      6
           tf.keras.layers.Conv2D(64, (3, 3), padding = 'same', activation='relu'), # Second convolutional layer
      7
      8
            tf.keras.layers.MaxPooling2D(2, 2), # Max-pooling layer
      9
           tf.keras.layers.Conv2D(128, (3, 3), padding = 'same', activation='relu'), # Third convolutional layer
     10
           tf.keras.layers.MaxPooling2D(2, 2), # Max-pooling layer
           tf.keras.layers.Conv2D(256, (3, 3), padding = 'same', activation='relu'), # Fourth convolutional layer
     11
           tf.keras.layers.MaxPooling2D(2, 2), # Max-pooling layer
     12
     13
           tf.keras.layers.BatchNormalization(),
           tf.keras.layers.Flatten(), # Flatten the feature maps
     14
           tf.keras.layers.Dense(512, activation='relu'), # Fully connected layer with 512 units
     15
     16
           tf.keras.layers.Dense(2, activation='softmax') # Output layer for categorical classification
     17 ])
```



→ Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 150, 150, 32)	896
max_pooling2d (MaxPooling2D)	(None, 75, 75, 32)	0
conv2d_1 (Conv2D)	(None, 75, 75, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 37, 37, 64)	0
conv2d_2 (Conv2D)	(None, 37, 37, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 18, 18, 128)	0
conv2d_3 (Conv2D)	(None, 18, 18, 256)	295,168
max_pooling2d_3 (MaxPooling2D)	(None, 9, 9, 256)	0
batch_normalization (BatchNormalization)	(None, 9, 9, 256)	1,024
flatten (Flatten)	(None, 20736)	0
dense (Dense)	(None, 512)	10,617,344
dense_1 (Dense)	(None, 2)	1,026

Total params: 11,007,810 (41.99 MB) Trainable params: 11,007,298 (41.99 MB) Non-trainable params: 512 (2.00 KB)

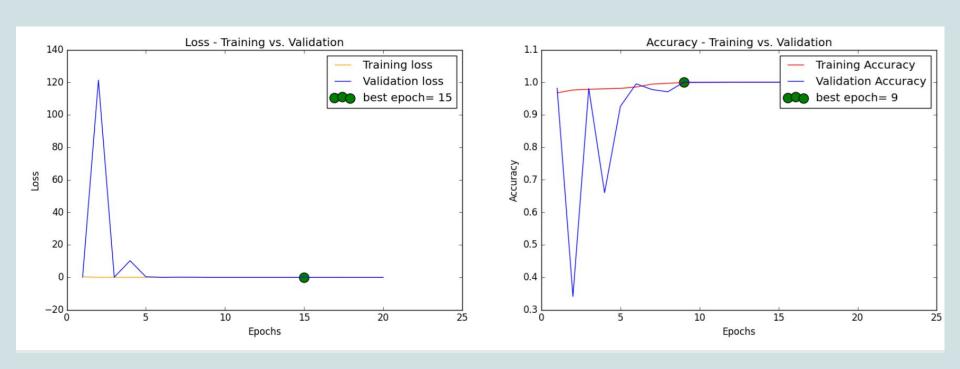
```
1 tensorboard = tf.keras.callbacks.TensorBoard(log dir = 'logs')
2 checkpoint = tf.keras.callbacks.ModelCheckpoint("cancer.keras", monitor="val loss", save best only=True, mode="auto", verbose = 1)
3 reduce lr on plateau = tf.keras.callbacks.ReduceLROnPlateau(monitor = 'val loss', factor = 0.3, patience = 2, min delta = 0.001,
                                mode='auto', verbose = 1)
4
5 early stopping = callbacks.EarlyStopping(monitor='val loss', patience=5, mode='min', restore best weights=True)
1 # cnn model.compile(optimizer='adam', loss='categorical crossentropy', metrics=['accuracy'])
                                                                                                        # TS - initial variant
2 cnn model.compile(optimizer='adam', loss='sparse categorical crossentropy', metrics=['accuracy'])
3
1 # history = cnn model.fit(train ds, validation data = val ds, epochs = 10, batch size = 32, verbose = 1,
                 callbacks=[tensorboard, checkpoint, early stopping, reduce lr on plateau])
2 #
3
4 # history = cnn model.fit(train ds, validation data = val ds, epochs = 20, batch size = 32, verbose = 1,
                 callbacks=[tensorboard, checkpoint, early stopping, reduce_lr_on_plateau])
5 #
6
7 history = cnn model.fit(train ds, validation data = val ds, epochs = 40, batch size = 32, verbose = 1,
               callbacks=[tensorboard, checkpoint, early stopping, reduce lr on plateau])
8
9
```

```
[18] 374/375 — Os 27ms/step - accuracy: 1.0000 - loss: 9.7650e-04
  Epoch 16: val loss did not improve from 0.00084
375/375 — 10s 28ms/step - accuracy: 1.0000 - loss: 9.7691e-04 - val_accuracy: 1.0000 - val_loss: 0.0010 - learning_rate: 2.4300e-06
   Epoch 17/40
   Epoch 17: val loss did not improve from 0.00084
   Epoch 17: ReduceLROnPlateau reducing learning rate to 7.289999985005124e-07.
   Epoch 18/40
   Epoch 18: val loss did not improve from 0.00084
   Epoch 19/40
   374/375 ———— 0s 27ms/step - accuracy: 1.0000 - loss: 0.0010
   Epoch 19: val loss did not improve from 0.00084
   Epoch 19: ReduceLROnPlateau reducing learning rate to 2.1870000637136398e-07.
   Epoch 20/40
   374/375 ----- 0s 27ms/step - accuracy: 1.0000 - loss: 9.2422e-04
   Epoch 20: val loss did not improve from 0.00084
   375/375 — 10s 28ms/step - accuracy: 1.0000 - loss: 9.2466e-04 - val accuracy: 1.0000 - val loss: 9.7114e-04 - learning rate: 2.1870e<sup>1</sup>
```

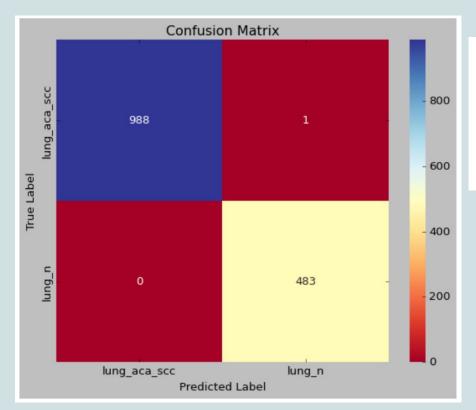
### **EVALUATION**

Test Accuracy: 0.9993206262588501

### **MODEL PERFORMANCE**

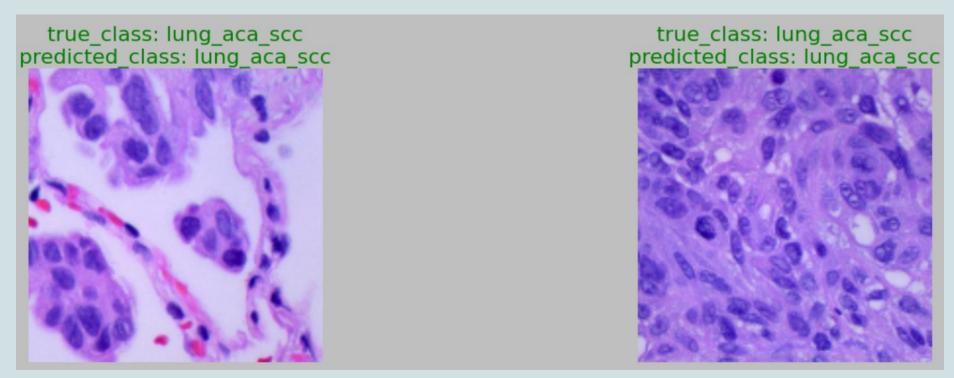


## **Confusion Matrix**



	precision	recall	f1-score	support	
0	1.00	1.00	1.00	989	
1	1.00	1.00	1.00	483	
accuracy			1.00	1472	
macro avg	1.00	1.00	1.00	1472	
weighted avg	1.00	1.00	1.00	1472	

## **Predictions**



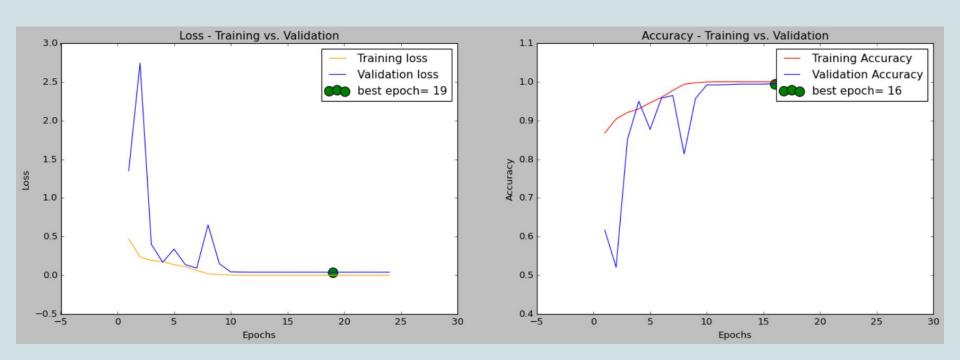
## **Predictions**



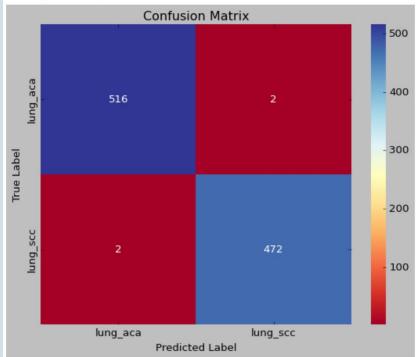
true\_class: lung\_aca\_scc predicted\_class: lung\_aca\_scc

### STRATEGY 2 - aca vs. scc

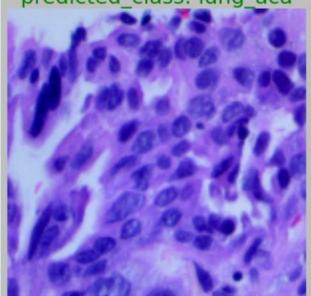
```
250/250 -----
             ----- 0s 7ms/step - accuracy: 0.9943 - loss: 0.0340
            Train Loss: 0.0015269367722794414
Train Accuracy: 0.9994990229606628
Val Loss: 0.039725691080093384
Val Accuracy: 0.9939516186714172
Test Loss: 0.021339187398552895
Test Accuracy: 0.9959677457809448
```



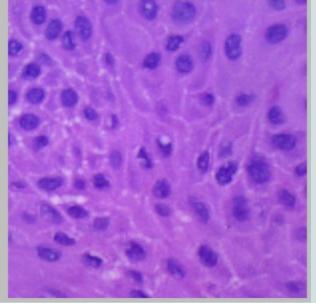
	precision	recall	f1-score	support
0	1.00	1.00	1.00	518
1	1.00	1.00	1.00	474
accuracy			1.00	992
macro avg	1.00	1.00	1.00	992
weighted avg	1.00	1.00	1.00	992



true\_class: lung\_aca predicted\_class: lung\_aca



true\_class: lung\_scc predicted\_class: lung\_scc

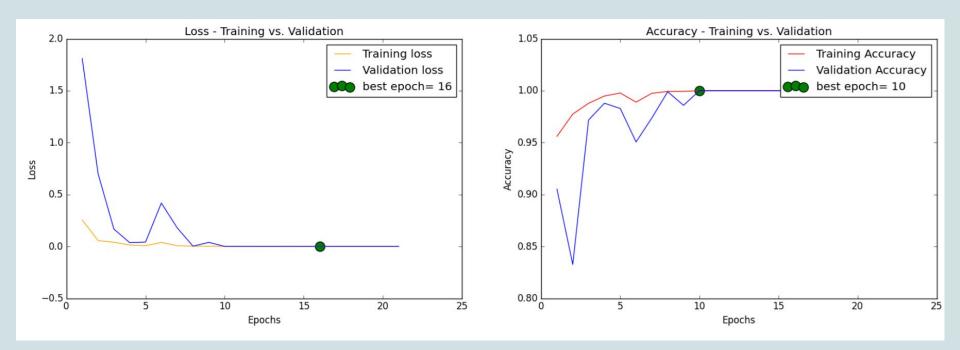


## STRATEGY 3 - lung aca vs. n

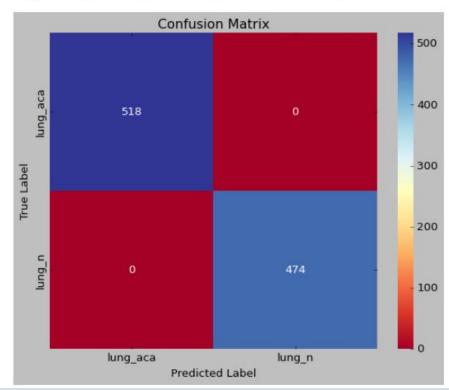
```
250/250 — 3s 11ms/step - accuracy: 1.0000 - loss: 1.6696e-04
31/31 — 9s 7ms/step - accuracy: 1.0000 - loss: 1.4585e-04
31/31 — 16s 10ms/step - accuracy: 1.0000 - loss: 2.2074e-04
Train Loss: 0.00015198372420854867
Train Accuracy: 1.0

Val Loss: 0.00010955912875942886
Val Accuracy: 1.0

Test Loss: 0.00022429967066273093
Test Accuracy: 1.0
```



support	f1-score	recall	precision	
518	1.00	1.00	1.00	0
474	1.00	1.00	1.00	1
992	1.00			accuracy
992	1.00	1.00	1.00	macro avg
992	1.00	1.00	1.00	weighted avg



true\_class: lung\_aca predicted\_class: lung\_aca

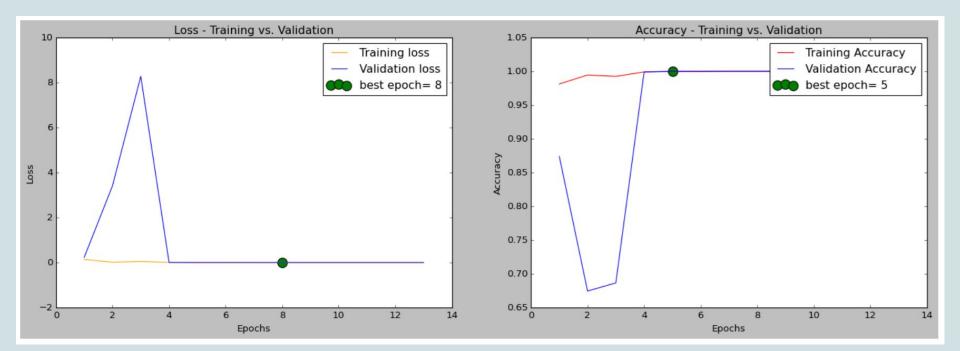


## STRATEGY 4 - lung scc vs. n

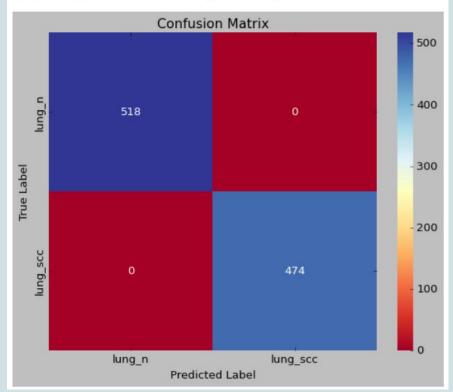
```
250/250 — 2s 10ms/step - accuracy: 1.0000 - loss: 2.4848e-05
31/31 — 0s 7ms/step - accuracy: 1.0000 - loss: 5.2482e-06
31/31 — 17s 10ms/step - accuracy: 1.0000 - loss: 3.1497e-04
Train Loss: 1.7837957784649916e-05
Train Accuracy: 1.0

Val Loss: 3.531769380060723e-06
Val Accuracy: 1.0

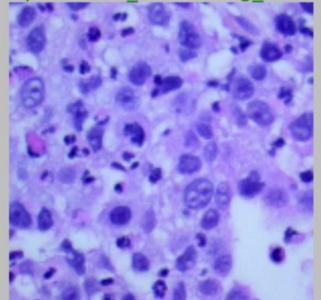
Test Loss: 0.0001346710487268865
Test Accuracy: 1.0
```



	precision	recall	f1-score	support	
0	1.00	1.00	1.00	518	
1	1.00	1.00	1.00	474	
accuracy			1.00	992	
macro avg	1.00	1.00	1.00	992	
weighted avg	1.00	1.00	1.00	992	

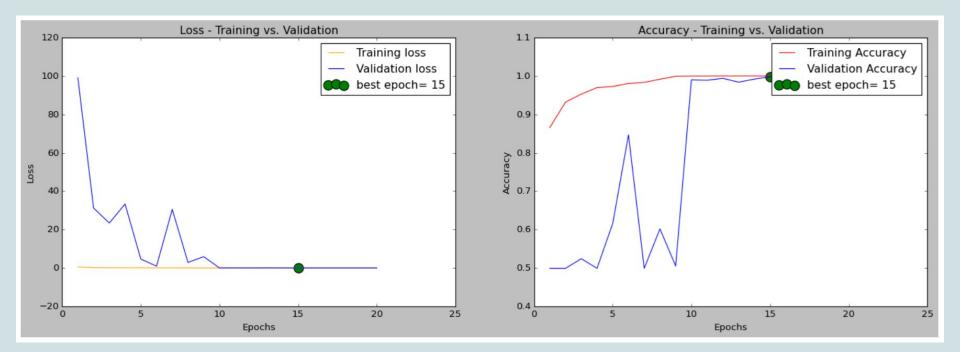


true\_class: lung\_scc predicted\_class: lung\_scc

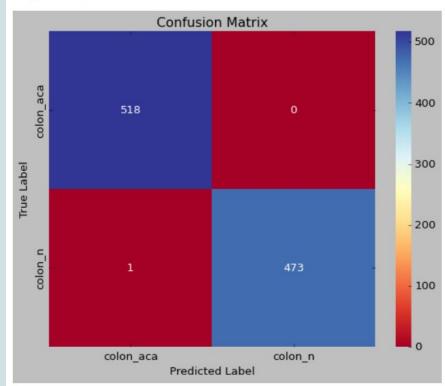


true\_class: lung\_n predicted\_class: lung\_n

### STRATEGY 5 - colon aca vs. n



	precision	recall	f1-score	support	
Ø	1.00	1.00	1.00	518	
1	1.00	1.00	1.00	474	
accuracy			1.00	992	
macro avg	1.00	1.00	1.00	992	
weighted avg	1.00	1.00	1.00	992	



true\_class: colon\_aca predicted\_class: colon\_aca

