Histopathologic Cancer Detection

The goal of this Kaggle competition is to create an algorithm to identify metastatic cancer in small image patches. The Kaggle competition is availble here: https://www.kaggle.com/competitions/histopathologic-cancer-detection/overview

From the data overview, we learn that images in the training set are only identified as class '1' when cancer is detected in the middle 32x32 pixels. This means we can use convolutional techniques that result in loss of features outside that area.

Initializaiton

```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.model_selection import train_test_split

from tensorflow.keras import layers, models
from PIL import Image
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.losses import categorical_crossentropy
from tensorflow.keras.losses import sparse_categorical_crossentropy
from tensorflow.keras.callbacks import EarlyStopping
```

```
initial_df = pd.read_csv('/content/Dataset/train_labels.csv', dtype=str)
train_img = '/content/Dataset/train'
test_img = '/content/Dataset/test'
test_df = pd.read_csv('/content/Dataset/sample_submission.csv', dtype=str)
```

```
initial_df['file'] = initial_df['id'] + '.tif'
test_df['file'] = test_df['id'] + '.tif'
```

Exploratory Analysis

Inspect an example image, get image size, and evaluate the distribution of labels.

```
initial_df.head()
```

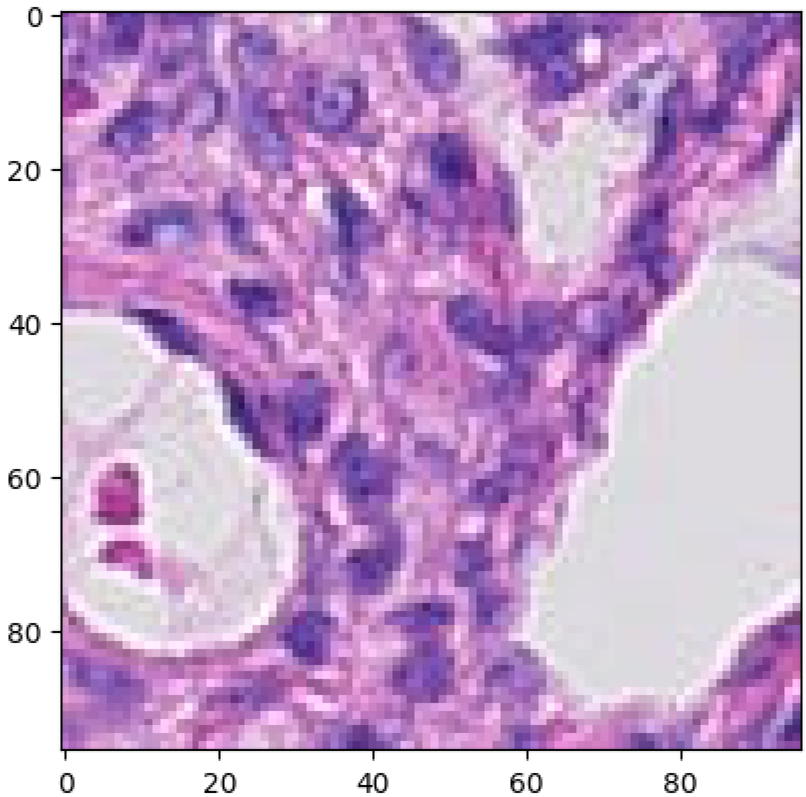
	id	label	
0	f38a6374c348f90b587e046aac6079959adf3835	0	f38a6374c348f90b587e046aac6079959a
1	c18f2d887b7ae4f6742ee445113fa1aef383ed77	1	c18f2d887b7ae4f6742ee445113fa1aef38
2	755db6279dae599ebb4d39a9123cce439965282d	0	755db6279dae599ebb4d39a9123cce43996
3	bc3f0c64fb968ff4a8bd33af6971ecae77c75e08	0	bc3f0c64fb968ff4a8bd33af6971ecae77c
4	068aba587a4950175d04c680d38943fd488d6a9d	0	068aba587a4950175d04c680d38943fd488

```
initial_df.describe()
```

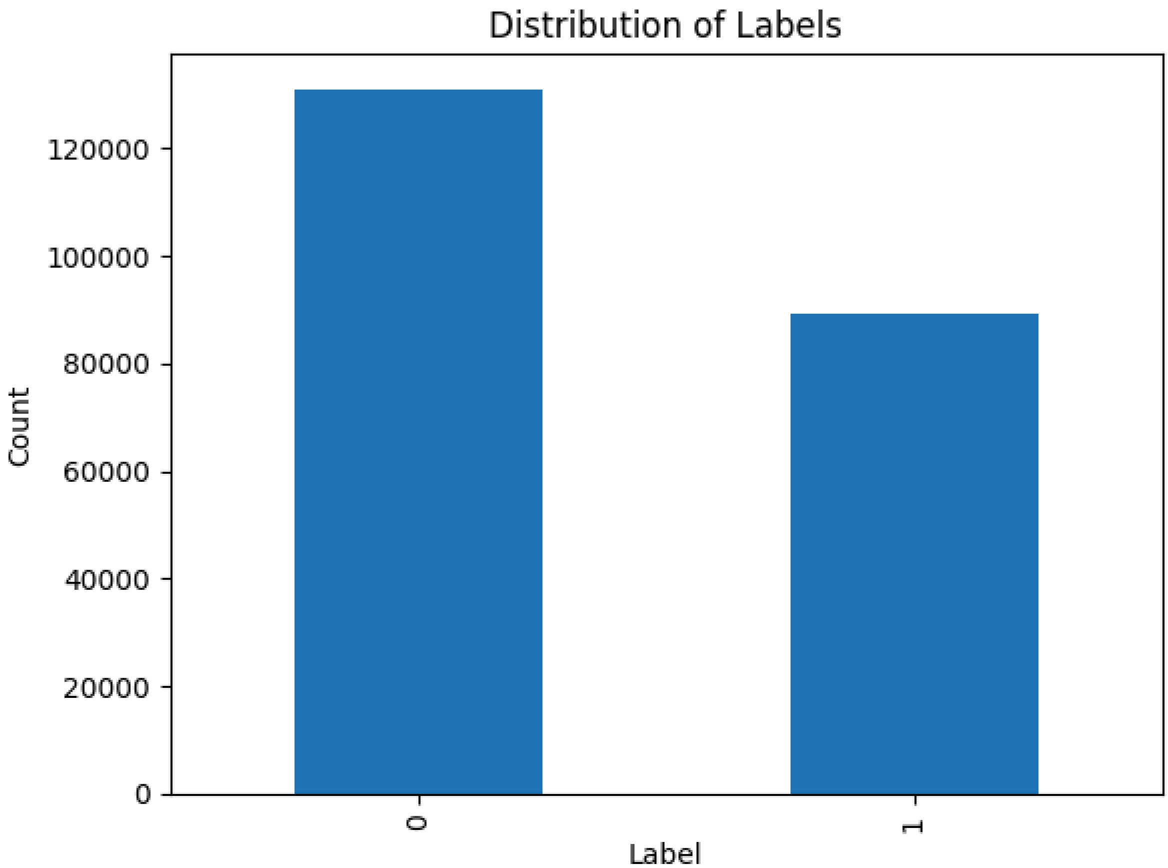
	id	label
count	220025	220025
unique	220025	2
top	a81f84895ddcd522302ddf34be02eb1b3e5af1cb	0
freq	1	130908

```
example_path = "/content/Dataset/train/a81f84895ddcd522302ddf34be02eb1b3e5af1cb.tif"
example_img = Image.open(example_path)
example_array = np.array(example_img)
print(f"Image Shape = {example_array.shape}")
plt.imshow(example_img)
plt.show()
```

```
Image Shape = (96, 96, 3)
```




```
# Count the occurrences of each class
class_counts = initial_df['label'].value_counts()

# Create a bar plot
class_counts.plot(kind='bar')

# Add labels and title
plt.xlabel('Label')
plt.ylabel('Count')
plt.title('Distribution of Labels')

# Show the plot
plt.show()
```




```
train_df, valid_df = train_test_split(initial_df, test_size=0.2, random_state=121, stratify=

print(train_df.shape)
print(valid_df.shape)
```

```
(176020, 3)
(44005, 3)
```

We have over 200,000 images to work with - plenty of data to train a model. We may need to sample the images for training if the volume becomes an issue. Each image is 96 pixels square. Considering that only the middle 32 pixel square contributes to the classification, we are safe to use convolutional techniques that result in data loss around the edges. The classes are also fairly balanced (60% '0' and 40% '1') so I won't take any special precautions other than stratifying by label when I create the validation dataset.

Image Handling Prep

```
train_image = ImageDataGenerator(rescale=1/255)
valid_image = ImageDataGenerator(rescale=1/255)
test_image = ImageDataGenerator(rescale=1/255)
```

```
img_h = 96
img_w = 96
batch_size = 128

train_flow = train_image.flow_from_dataframe(
    dataframe=train_df,
    directory=train_img,
    batch_size=batch_size,
    x_col='file',
    y_col='label',
    class_mode='binary',
    target_size=(img_h, img_w),
    shuffle=True,
    seed=121
)

valid_flow = valid_image.flow_from_dataframe(
    dataframe=valid_df,
    directory=train_img,
    batch_size=batch_size,
    x_col='file',
    y_col='label',
    class_mode='binary',
    target_size=(img_h, img_w),
    shuffle=True,
    seed=121
)

test_flow = test_image.flow_from_dataframe(
    dataframe=test_df,
    directory=test_img,
    batch_size=batch_size,
    x_col='file',
    y_col=None,
    class_mode=None,
    target_size=(img_h, img_w),
    shuffle=False)
```

```
Found 176020 validated image filenames belonging to 2 classes.
Found 44005 validated image filenames belonging to 2 classes.
Found 57458 validated image filenames.
```

Initial Model Creation

This basic architecture uses alternating 3x3 convolutional layers and max pool layers. Convolutional layers serve to extract increasingly complex features from the images. Max pooling is an efficient way to reduce features and provides some translation invariance. The flatten layers serves to transition from feature extraction to the classification task. Dense layers require 1-dimensional input. The prediction is made in the final dense layer.

```
model = models.Sequential()
model.add(layers.Input(shape=(img_h, img_w, 3)))
model.add(layers.Conv2D(32, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(1, activation = 'sigmoid'))


model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 94, 94, 32)	896
max_pooling2d (MaxPooling2D)	(None, 47, 47, 32)	0
conv2d_1 (Conv2D)	(None, 45, 45, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 22, 22, 64)	0
conv2d_2 (Conv2D)	(None, 20, 20, 64)	36,928
flatten (Flatten)	(None, 25600)	0
dense (Dense)	(None, 64)	1,638,464
dense_1 (Dense)	(None, 1)	65

```
Total params: 1,694,849 (6.47 MB)
Trainable params: 1,694,849 (6.47 MB)
Non-trainable params: 0 (0.00 B)
```

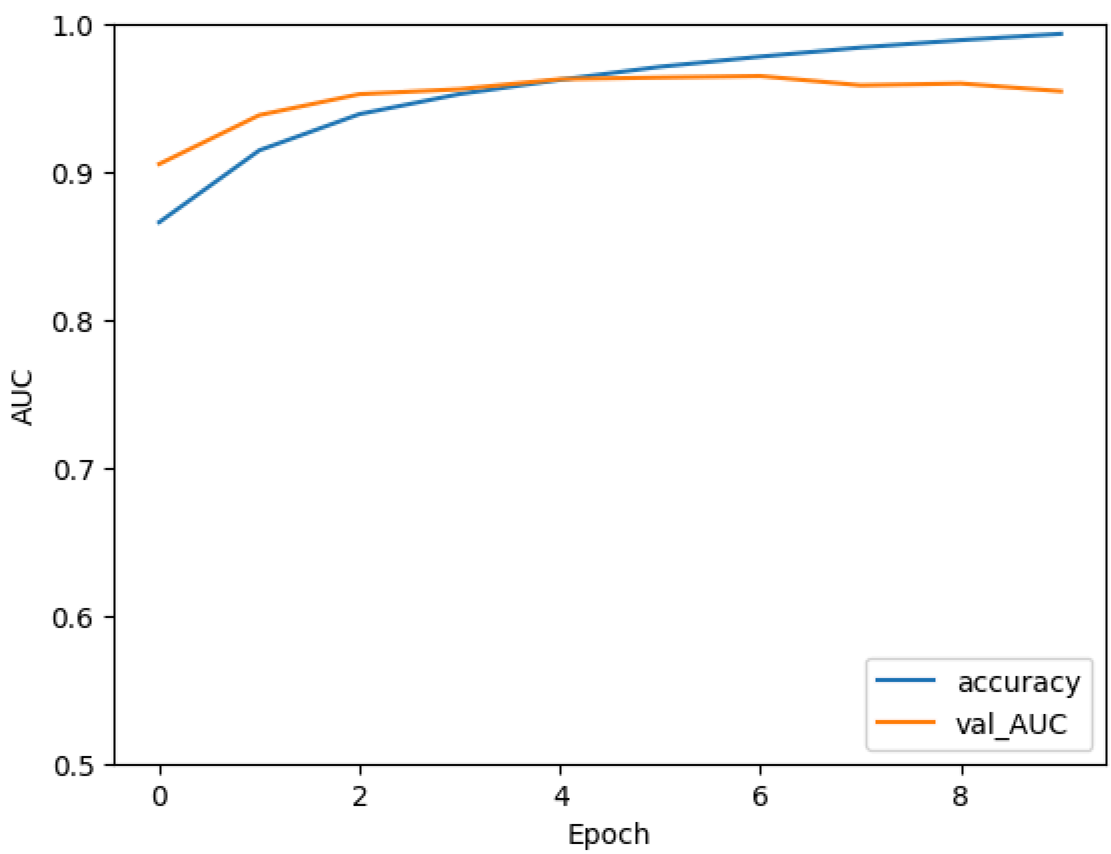
```
model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy', 'AUC'])

history = model.fit(train_flow, epochs=10,
                    validation_data=valid_flow)
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adap
  self._warn_if_super_not_called()
Epoch 1/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 338s 241ms/step - AUC: 0.8329 - accuracy: 0.7632 - loss:
Epoch 2/10
```

```
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 252s 183ms/step - AUC: 0.9070 - accuracy: 0.8357 - loss:
Epoch 3/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 233s 169ms/step - AUC: 0.9353 - accuracy: 0.8673 - loss:
Epoch 4/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 226s 164ms/step - AUC: 0.9517 - accuracy: 0.8877 - loss:
Epoch 5/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 234s 170ms/step - AUC: 0.9623 - accuracy: 0.9015 - loss:
Epoch 6/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 251s 182ms/step - AUC: 0.9714 - accuracy: 0.9169 - loss:
Epoch 7/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 260s 189ms/step - AUC: 0.9781 - accuracy: 0.9282 - loss:
Epoch 8/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 234s 170ms/step - AUC: 0.9846 - accuracy: 0.9405 - loss:
Epoch 9/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 242s 176ms/step - AUC: 0.9897 - accuracy: 0.9520 - loss:
Epoch 10/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 258s 188ms/step - AUC: 0.9942 - accuracy: 0.9662 - loss:
```

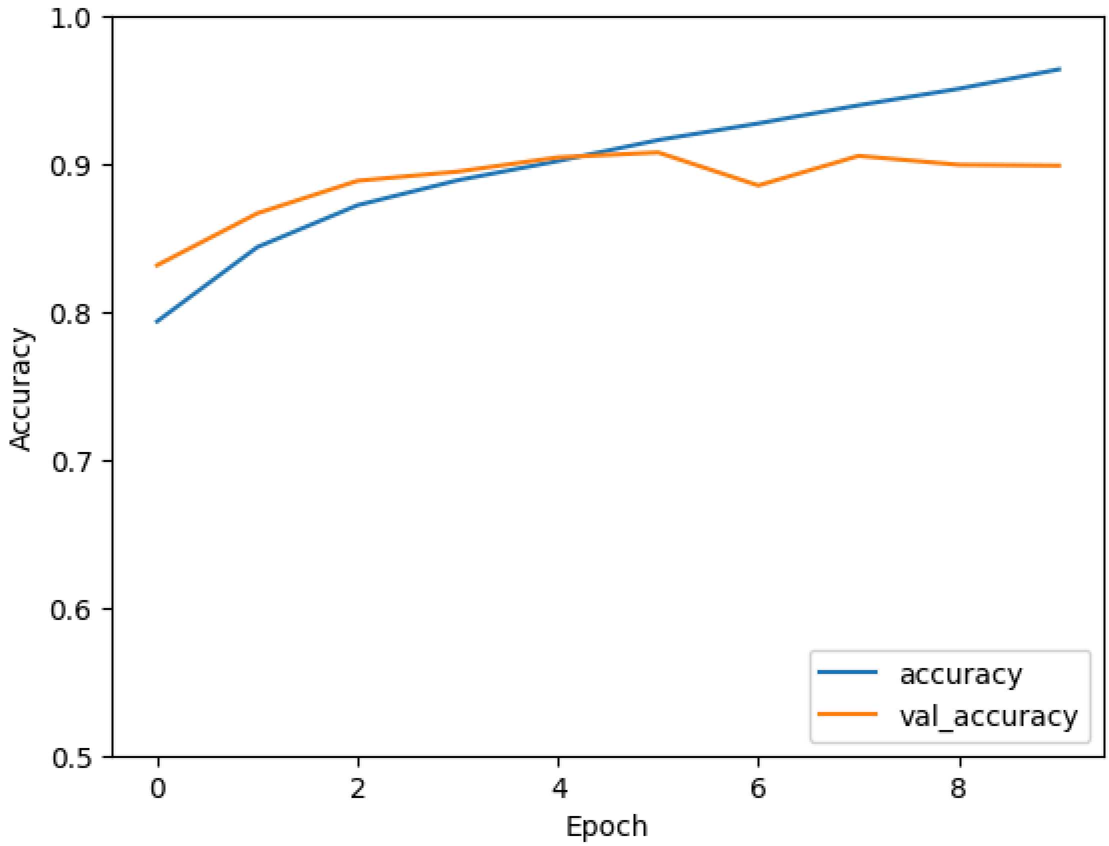
```python
plt.plot(history.history['AUC'], label='accuracy')
plt.plot(history.history['val_AUC'], label = 'val_AUC')
plt.xlabel('Epoch')
plt.ylabel('AUC')
plt.ylim([0.5, 1])
plt.legend(loc='lower right')
```

```
<matplotlib.legend.Legend at 0x786f603f5790>
```



```
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.ylim([0.5, 1])
plt.legend(loc='lower right')
```

```
<matplotlib.legend.Legend at 0x786ef47aa8d0>
```




```
test_pred = model.predict(test_flow)
test_pred = test_pred.reshape(-1)
test_pred.shape
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adap
  self._warn_if_super_not_called()
449/449 ━━━━━━━━━━━━━━━━━━━━ 81s 176ms/step
(57458,)
```

```
test_df['label'] = test_pred
submit_df = test_df[['id', 'label']]
submit_df.to_csv('/content/submission-simple.csv', index=False)

# 0.8965 test score.
```

Early Stopping

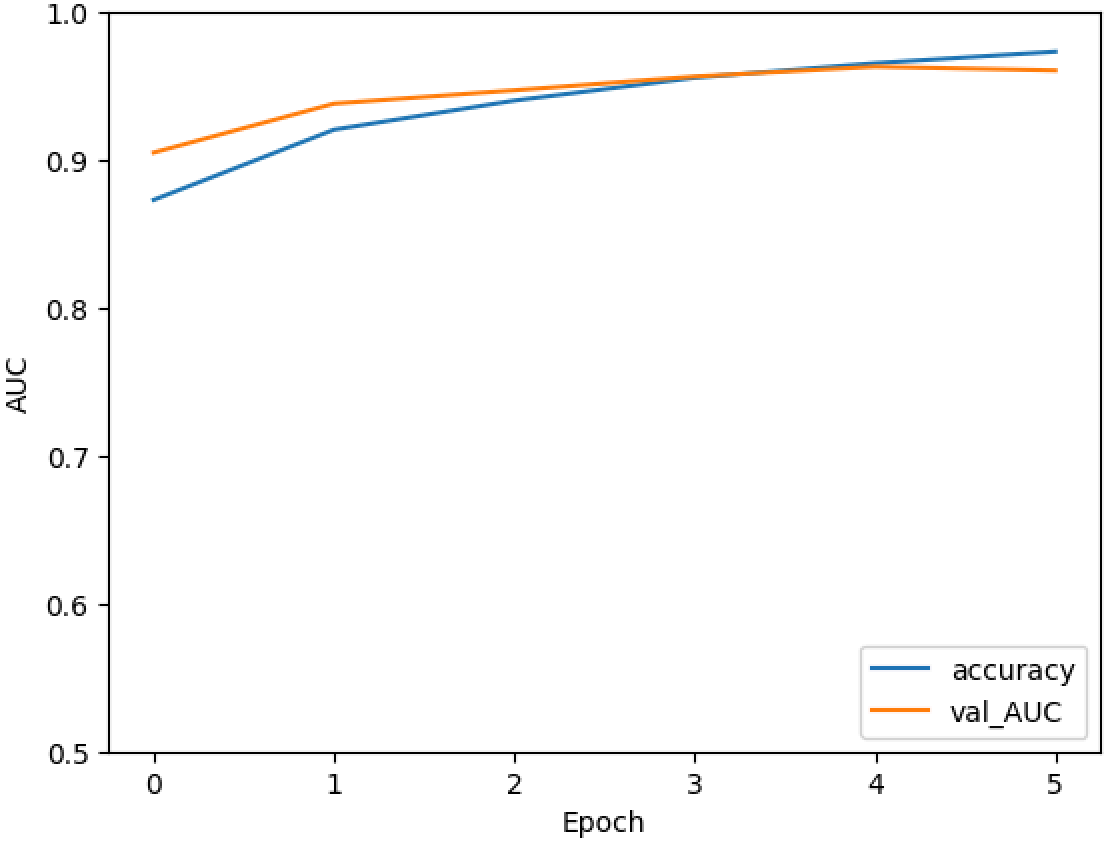
The model performed really well, with a maximum validation AUC of of 0.96 and a test score of 0.8965 when submitted to Kaggle. We do see a bit of overfitting and a need for early stopping - preferably after epoch 7. In the next section, I'll add in early stopping.

```
model = models.Sequential()
model.add(layers.Input(shape=(img_h, img_w, 3)))
model.add(layers.Conv2D(32, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(1, activation = 'sigmoid'))


# Adding in Early Stopping
model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy', 'AUC'])

callback = EarlyStopping(monitor='val_AUC',
                         patience=1,
    verbose=0,
    mode='auto',
    baseline=None,
    restore_best_weights=True,
    start_from_epoch=2
)

history = model.fit(train_flow, epochs=10,
                    validation_data=valid_flow, callbacks=[callback])
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adap
  self._warn_if_super_not_called()
Epoch 1/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 346s 247ms/step - AUC: 0.8375 - accuracy: 0.7653 - loss:
Epoch 2/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 267s 194ms/step - AUC: 0.9117 - accuracy: 0.8401 - loss:
Epoch 3/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 294s 174ms/step - AUC: 0.9367 - accuracy: 0.8668 - loss:
Epoch 4/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 247s 179ms/step - AUC: 0.9538 - accuracy: 0.8893 - loss:
Epoch 5/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 238s 173ms/step - AUC: 0.9650 - accuracy: 0.9046 - loss:
Epoch 6/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 240s 174ms/step - AUC: 0.9739 - accuracy: 0.9204 - loss:
```

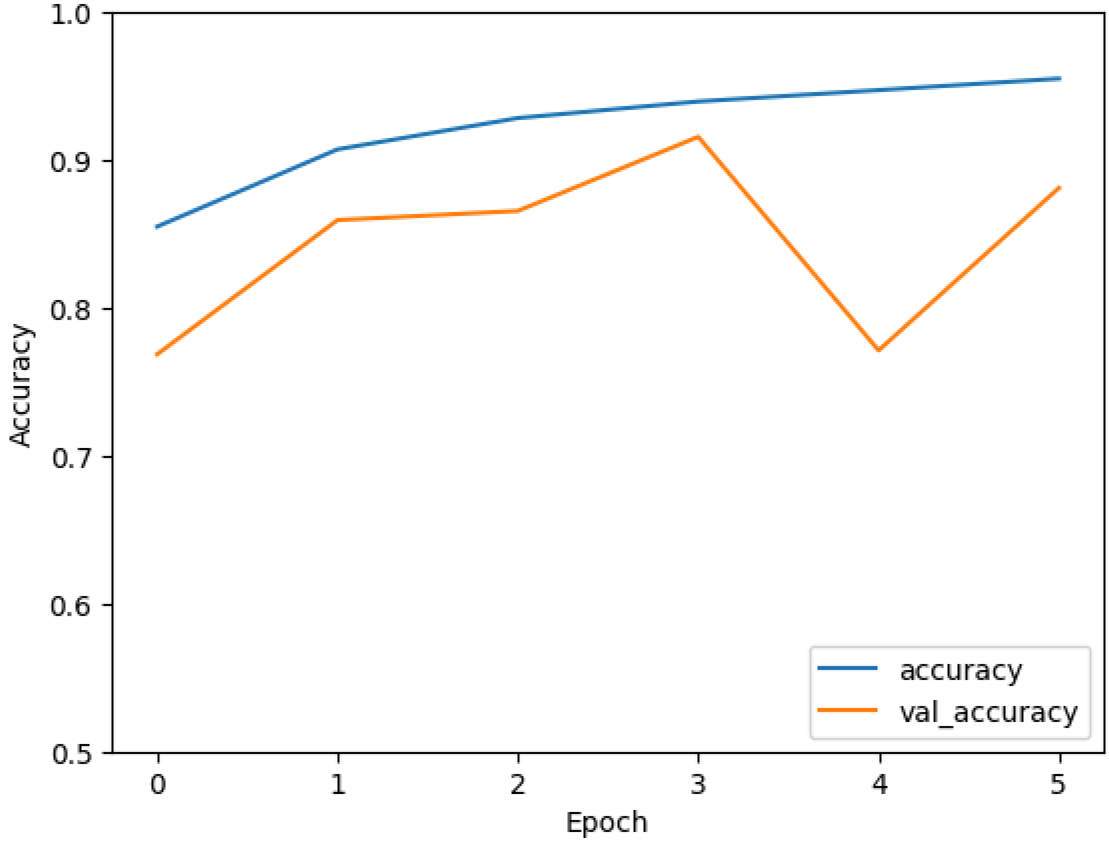
```
plt.plot(history.history['AUC'], label='accuracy')
plt.plot(history.history['val_AUC'], label = 'val_AUC')
plt.xlabel('Epoch')
plt.ylabel('AUC')
plt.ylim([0.5, 1])
plt.legend(loc='lower right')
```

```
<matplotlib.legend.Legend at 0x78a413bd1190>
```




```
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.ylim([0.5, 1])
plt.legend(loc='lower right')
```

```
<matplotlib.legend.Legend at 0x78a3aed89190>
```




```
test_pred = model.predict(test_flow)
test_pred = test_pred.reshape(-1)
test_df['label'] = test_pred
submit_df = test_df[['id', 'label']]
submit_df.to_csv('/content/submission-simple-early.csv', index=False)

# 0.9213 test score.
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adap
  self._warn_if_super_not_called()
449/449 ━━━━━━━━━━━━━━━━━━━━ 101s 221ms/step
```

More Complex Model Architecture

The update model architecture follows the same general pattern but I've added batch normalization between the convolutional and pooling layers. I added an additional convolution layer and max filter size of the convolutional layers now goes to 256. Finally, I added a dropout layer between the next-to-last dense layer and the output layer. The batch normalization helps accelerate and stabilize training while the dropout layer curbs overfitting. Dropout layers are typically added amongst dense layers but can also be added after convolutional layers.

```
model = models.Sequential()
model.add(layers.Input(shape=(img_h, img_w, 3)))
model.add(layers.Conv2D(32, (3, 3), activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3), activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(256, (3, 3), activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dropout(0.3))
model.add(layers.Dense(1, activation = 'sigmoid'))


model.summary()
```

```
Model: "sequential_1"
```

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 94, 94, 32)	896
batch_normalization (BatchNormalization)	(None, 94, 94, 32)	128
max_pooling2d_2 (MaxPooling2D)	(None, 47, 47, 32)	0
conv2d_4 (Conv2D)	(None, 45, 45, 64)	18,496
batch_normalization_1 (BatchNormalization)	(None, 45, 45, 64)	256
max_pooling2d_3 (MaxPooling2D)	(None, 22, 22, 64)	0
conv2d_5 (Conv2D)	(None, 20, 20, 128)	73,856
batch_normalization_2 (BatchNormalization)	(None, 20, 20, 128)	512
max_pooling2d_4 (MaxPooling2D)	(None, 10, 10, 128)	0
conv2d_6 (Conv2D)	(None, 8, 8, 256)	295,168
batch_normalization_3 (BatchNormalization)	(None, 8, 8, 256)	1,024
max_pooling2d_5 (MaxPooling2D)	(None, 4, 4, 256)	0
flatten_1 (Flatten)	(None, 4096)	0
dense_2 (Dense)	(None, 64)	262,208
dropout (Dropout)	(None, 64)	0
dense_3 (Dense)	(None, 1)	65

Total params: 1,955,909 (7.46 MB)
Trainable params: 651,649 (2.49 MB)
Non-trainable params: 960 (3.75 KB)
Optimizer params: 1,303,300 (4.97 MB)

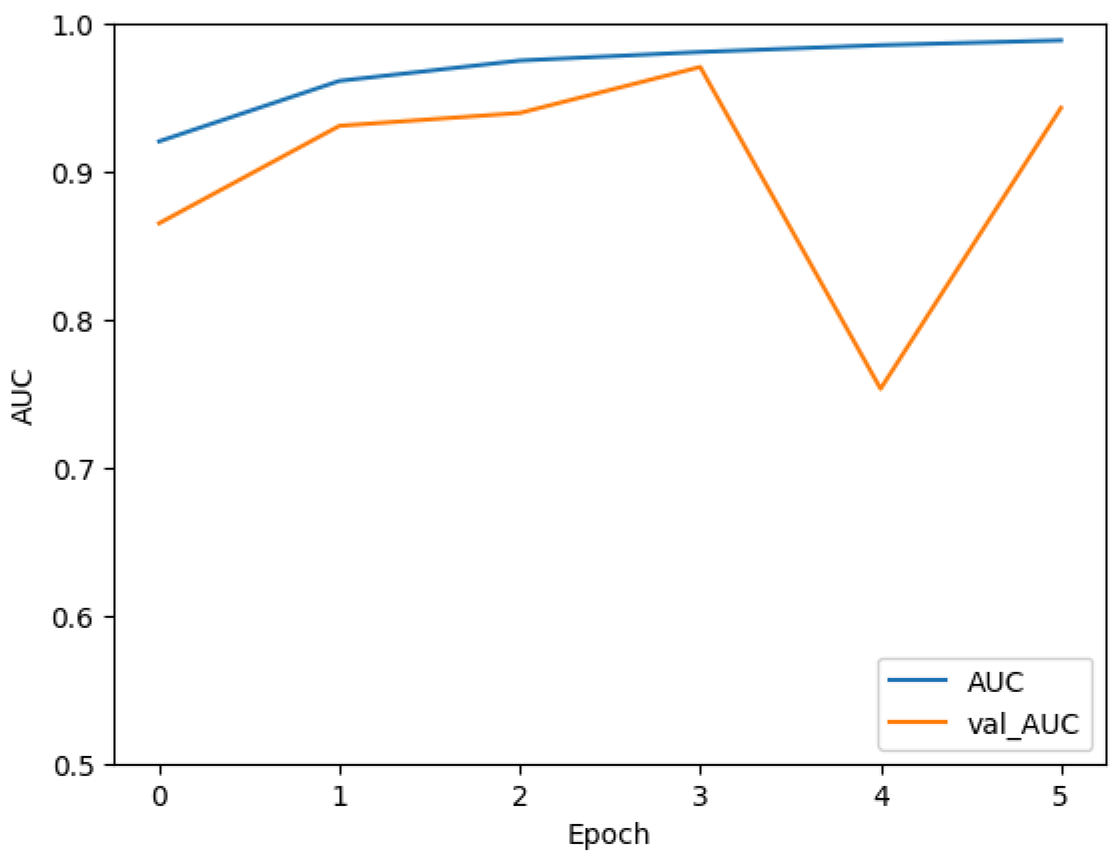
```
model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy', 'AUC'])

callback = EarlyStopping(monitor='val_AUC',
                         patience=2,
    verbose=0,
    mode='auto',
    baseline=None,
    restore_best_weights=True,
```

```
    start_from_epoch=2
)

history = model.fit(train_flow, epochs=10,
                    validation_data=valid_flow, callbacks=[callback])
```

```
Epoch 1/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 324s 229ms/step - AUC: 0.8880 - accuracy: 0.8247 - loss:
Epoch 2/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 257s 187ms/step - AUC: 0.9562 - accuracy: 0.9006 - loss:
Epoch 3/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 296s 215ms/step - AUC: 0.9737 - accuracy: 0.9262 - loss:
Epoch 4/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 252s 183ms/step - AUC: 0.9812 - accuracy: 0.9401 - loss:
Epoch 5/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 260s 189ms/step - AUC: 0.9851 - accuracy: 0.9470 - loss:
Epoch 6/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 263s 190ms/step - AUC: 0.9891 - accuracy: 0.9563 - loss:
```

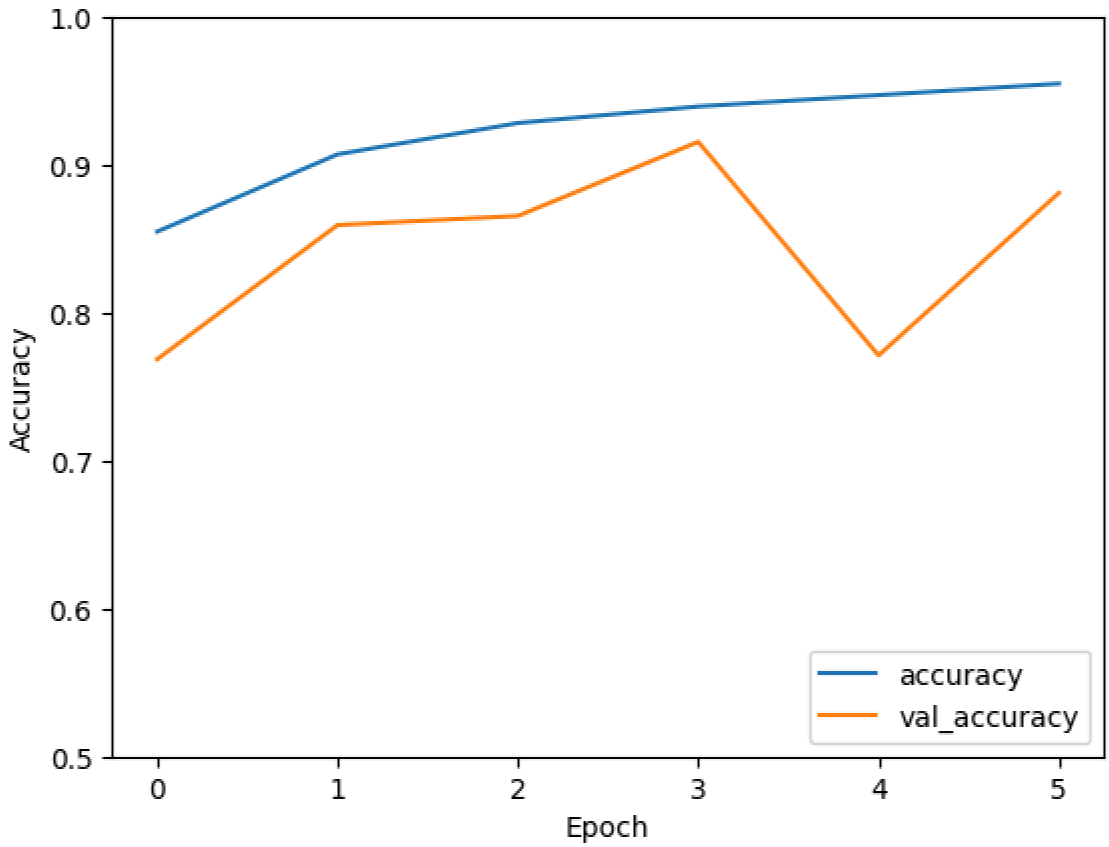
```
plt.plot(history.history['AUC'], label='AUC')
plt.plot(history.history['val_AUC'], label = 'val_AUC')
plt.xlabel('Epoch')
plt.ylabel('AUC')
plt.ylim([0.5, 1])
plt.legend(loc='lower right')
```

```
<matplotlib.legend.Legend at 0x78a39a421050>
```



```
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.ylim([0.5, 1])
plt.legend(loc='lower right')
```

```
<matplotlib.legend.Legend at 0x78a3905c9050>
```




```
test_pred = model.predict(test_flow)
test_pred = test_pred.reshape(-1)
test_df['label'] = test_pred
submit_df = test_df[['id', 'label']]
submit_df.to_csv('/content/submission-complex-early.csv', index=False)

# Test score 0.939
```

```
449/449 ━━━━━━━━━━━━━━━━━━━━ 103s 225ms/step
```

Optimizer Experimentation

I've decided to stick with the more complex model and see how the optimizer affects model performance. The lamb optimizer adds a trust ratio that scales the learning rate. It is designed to perform well with large batch sizes and may improve performance because I'm using a batch size of 128.

I also try the NAdam optimizer which is Adam with Nesterov momentum which anticipates future gradients.

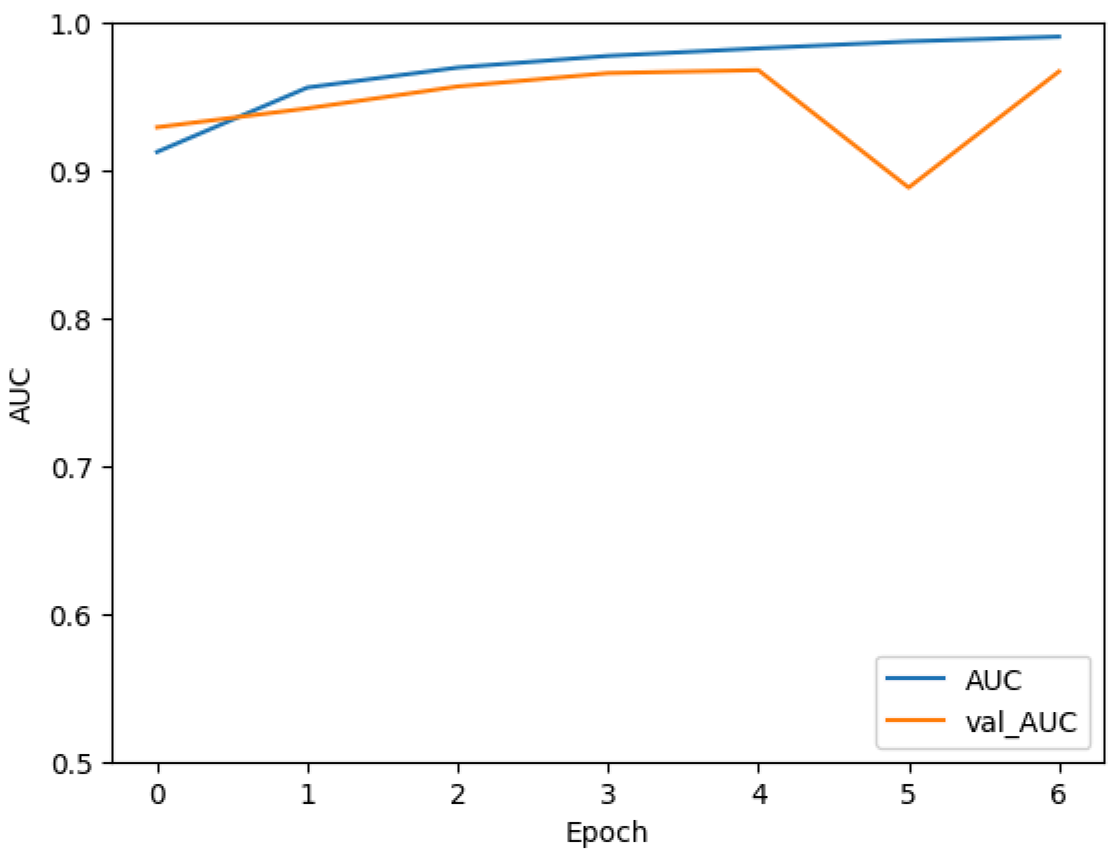
```
from tensorflow.keras.optimizers import Lamb

optimizer = Lamb(learning_rate=0.001, weight_decay=0.01)


model = models.Sequential()
model.add(layers.Input(shape=(img_h, img_w, 3)))
model.add(layers.Conv2D(32, (3, 3), activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3), activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(256, (3, 3), activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dropout(0.3))
model.add(layers.Dense(1, activation = 'sigmoid'))


model.compile(optimizer=optimizer,
              loss='binary_crossentropy',
              metrics=['accuracy', 'AUC'])

callback = EarlyStopping(monitor='val_AUC',
                         patience=2,
    verbose=0,
    mode='auto',
    baseline=None,
    restore_best_weights=True,
    start_from_epoch=2
)

history = model.fit(train_flow, epochs=10,
                    validation_data=valid_flow, callbacks=[callback])
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adap
  self._warn_if_super_not_called()
Epoch 1/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 398s 279ms/step - AUC: 0.8749 - accuracy: 0.8069 - loss:
```

```
Epoch 2/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 281s 204ms/step - AUC: 0.9515 - accuracy: 0.8881 - loss:
Epoch 3/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 299s 217ms/step - AUC: 0.9687 - accuracy: 0.9146 - loss:
Epoch 4/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 263s 191ms/step - AUC: 0.9771 - accuracy: 0.9281 - loss:
Epoch 5/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 284s 207ms/step - AUC: 0.9827 - accuracy: 0.9385 - loss:
Epoch 6/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 270s 196ms/step - AUC: 0.9872 - accuracy: 0.9483 - loss:
Epoch 7/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 337s 208ms/step - AUC: 0.9908 - accuracy: 0.9563 - loss:
```

```
plt.plot(history.history['AUC'], label='AUC')
plt.plot(history.history['val_AUC'], label = 'val_AUC')
plt.xlabel('Epoch')
plt.ylabel('AUC')
plt.ylim([0.5, 1])
plt.legend(loc='lower right')
```

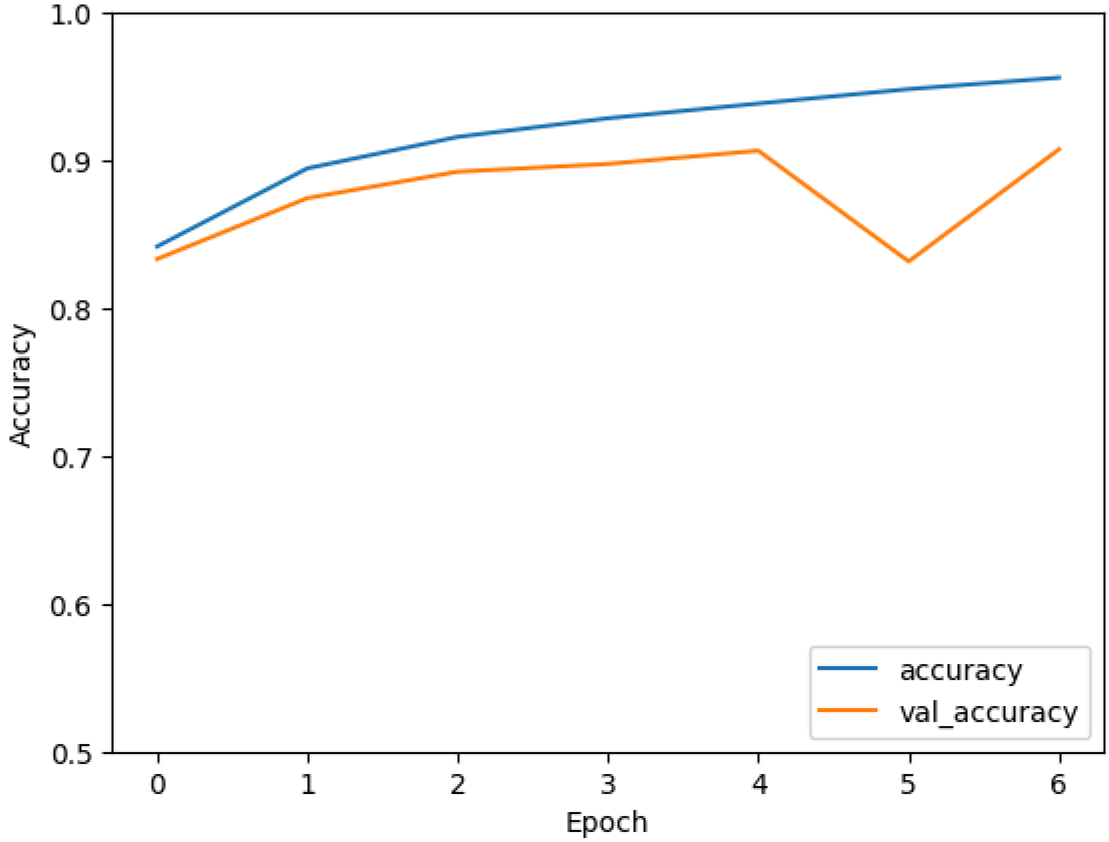
```
<matplotlib.legend.Legend at 0x785ff3afe390>
```




```
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
```

```
plt.ylim([0.5, 1])
plt.legend(loc='lower right')
```

<matplotlib.legend.Legend at 0x785fee6156d0>




```
test_pred = model.predict(test_flow)
test_pred = test_pred.reshape(-1)
test_df['label'] = test_pred
submit_df = test_df[['id', 'label']]
submit_df.to_csv('/content/submission-complex-early-lamb.csv', index=False)

# 0.9363 test score
```

449/449 ━━━━━━━━━━━━━━━━━━━━ **100s** 217ms/step

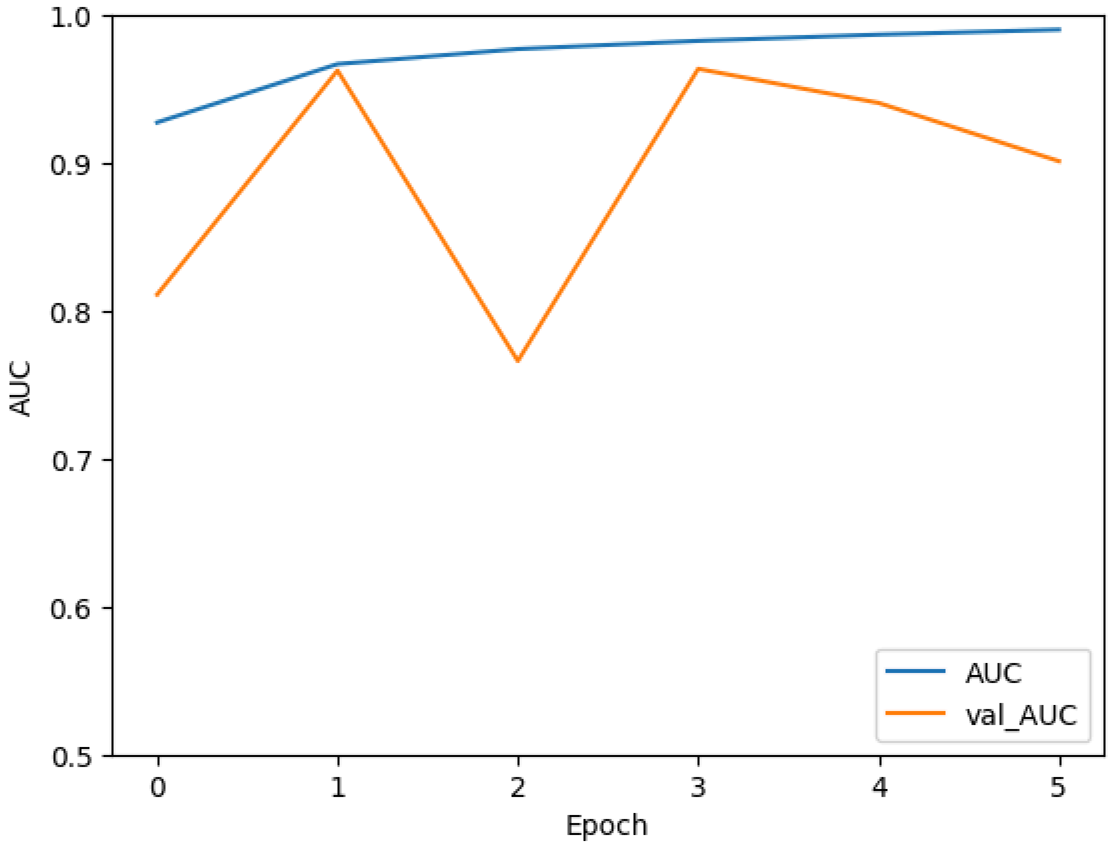
```
model = models.Sequential()
model.add(layers.Input(shape=(img_h, img_w, 3)))
model.add(layers.Conv2D(32, (3, 3), activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3), activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(256, (3, 3), activation='relu'))
```

```
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dropout(0.3))
model.add(layers.Dense(1, activation = 'sigmoid'))


# NAdam

model.compile(optimizer=tf.keras.optimizers.Nadam(learning_rate=0.001),
              loss='binary_crossentropy',
              metrics=['accuracy', 'AUC'])

callback = EarlyStopping(monitor='val_AUC',
                         patience=2,
    verbose=0,
    mode='auto',
    baseline=None,
    restore_best_weights=True,
    start_from_epoch=2
)

history = model.fit(train_flow, epochs=10,
                    validation_data=valid_flow, callbacks=[callback])
```

```
Epoch 1/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 325s 230ms/step - AUC: 0.8911 - accuracy: 0.8264 - loss:
Epoch 2/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 292s 212ms/step - AUC: 0.9647 - accuracy: 0.9114 - loss:
Epoch 3/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 271s 197ms/step - AUC: 0.9766 - accuracy: 0.9313 - loss:
Epoch 4/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 330s 203ms/step - AUC: 0.9830 - accuracy: 0.9425 - loss:
Epoch 5/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 286s 208ms/step - AUC: 0.9870 - accuracy: 0.9520 - loss:
Epoch 6/10
1376/1376 ━━━━━━━━━━━━━━━━━━━━ 279s 203ms/step - AUC: 0.9908 - accuracy: 0.9587 - loss:
```

```
plt.plot(history.history['AUC'], label='AUC')
plt.plot(history.history['val_AUC'], label = 'val_AUC')
plt.xlabel('Epoch')
plt.ylabel('AUC')
plt.ylim([0.5, 1])
plt.legend(loc='lower right')
```

```
<matplotlib.legend.Legend at 0x785fe6677450>
```




```
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.ylim([0.5, 1])
plt.legend(loc='lower right')
```

```
<matplotlib.legend.Legend at 0x785fe65bc0d0>
```