1 Original dataset modeling

Student name: Sam Oliver
Student pace: self-paced
Scheduled project review: 10/12/2022 1:30 PM EST
Instructor name: Abhineet Kulkarni

Preface for this notebook: If not already noted, please reference the README and preferably the STRIP.ipynb notebook (Google Colab notebook). There is information on this project, evaluation methods, notes on the datasets used, etc.

1.1 Dataset description

This notebook will focus on modeling with the [original dataset used in this Kaggle competition (https://www.kaggle.com/competitions/mayo-clinic-strip-ai/data)](https://www.kaggle.com/competitions/mayo-clinic-strip-ai/data). This dataset contains 1,158 different files with a size of about 400 GB. Here is a more detailed description found of each file and data field:

1. train - A folder containing images in the TIFF format to be used as training data.
2. test - A folder containing images to be used as test data. The actual test data comprises about 280 images.
3. train.csv Contains annotations for images in the train/ folder.

- image_id - A unique identifier for this instance having the form {patient_id}_{image_num}. Corresponds to the image {image_id}.tif.
- center_id - Identifies the medical center where the slide was obtained.
- patient_id - Identifies the patient from whom the slide was obtained.
- image_num - Enumerates images of clots obtained from the same patient.
- label - The etiology of the clot, either CE or LAA. This field is the classification target.

4. test.csv - Annotations for images in the test/ folder. Has the same fields as train.csv excluding label.
5. other.csv - Annotations for images in the other/ folder. Has the same fields as train.csv. The center_id is unavailable for these images however.

- label - The etiology of the clot, either Unknown or Other.
- other_specified - The specific etiology, when known, in case the etiology is labeled as Other.

6. sample_submission.csv - A sample submission file in the correct format.

1.2 Import packages and data

In [1]:

```
# Imports
import pandas as pd
import numpy as np
from pathlib import Path
import glob
import os
from os import listdir
from pathlib import Path

from skimage.io import imread
from PIL import Image
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
import cv2

%matplotlib inline

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator, load_
from tensorflow.keras.preprocessing.image import img_to_array
from tensorflow.keras import models, layers, optimizers, regularizers
from tensorflow.keras import activations
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.applications import VGG16, VGG19
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dropout
from tensorflow.keras.callbacks import ModelCheckpoint, ReduceLROnPlateau

from sklearn.metrics import confusion_matrix, classification_report
from sklearn.metrics import plot_confusion_matrix
from sklearn.model_selection import train_test_split

from keras.models import load_model
import keras.applications

import datetime
from tqdm import tqdm

from tensorflow.random import set_seed
set_seed(13)
```

In [2]:

```
train_df = pd.read_csv(r'C:\Users\18016\Downloads\train\.csv')
train_df.head()
```

Out[2]:

	image_id	center_id	patient_id	image_num	label
0	006388_0	11	006388	0	CE
1	008e5c_0	11	008e5c	0	CE
2	00c058_0	11	00c058	0	LAA
3	01adc5_0	11	01adc5	0	LAA
4	026c97_0	4	026c97	0	CE

Each patient has an id, each image has an id, the center id (0-11) is unique identifier for each center that contributed images to the registry. image_num references how many images are represented for the unique patient id. Label references whether the stroke occurred as cardioembolic or large artery atherosclerosis.

Append the paths for the images below.

In [3]:

```
train_path = r"C:\\Users\\18016\\Downloads\\train\\"
train_df["file_path"] = train_df["image_id"].apply(lambda x: train_path + x
train_df.head()
```

Out[3]:

	image_id	center_id	patient_id	image_num	label	file_path
0	006388_0	11	006388	0	CE	C:\\Users\\18016\\Downloads\\train\\006388_0.tif
1	008e5c_0	11	008e5c	0	CE	C:\\Users\\18016\\Downloads\\train\\008e5c_0.tif
2	00c058_0	11	00c058	0	LAA	C:\\Users\\18016\\Downloads\\train\\00c058_0.tif
3	01adc5_0	11	01adc5	0	LAA	C:\\Users\\18016\\Downloads\\train\\01adc5_0.tif
4	026c97_0	4	026c97	0	CE	C:\\Users\\18016\\Downloads\\train\\026c97_0.tif

OpenSlide package will allow for opening and processing of the Whole Slide images (the .tif images represented by the paths in the train_df file_path column).

Add openslide path for bin file. Need to add the dll directory file in so OpenSlide builds necessary references.

In [4]:

```
OPENSLIDE_PATH = r'C:\Users\18016\Desktop\openslide-win64-20220811\bin'

if hasattr(os, 'add_dll_directory'):
    # Python >= 3.8 on Windows
    with os.add_dll_directory(OPENSLIDE_PATH):
        import openslide
else:
    import openslide
```

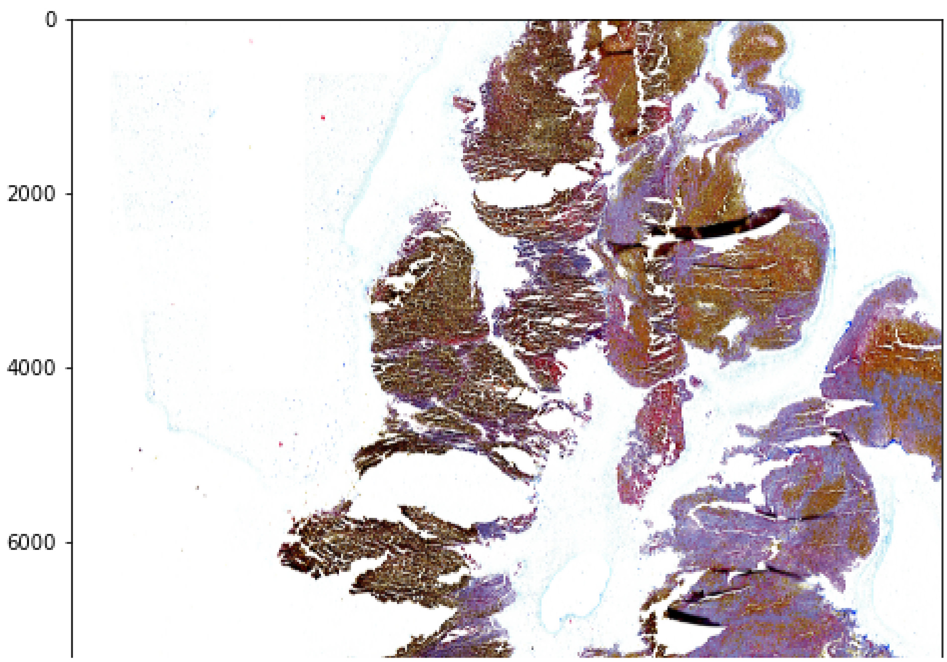
In [5]:

```
from openslide import OpenSlide
```

1.3 Preview some images

In [6]:

```python
sample_train = train_df[:5]

for i in range(5):
    slide = OpenSlide(sample_train.loc[i, "file_path"])
    region = (0, 0)
    size = (10000, 10000)
    region = slide.read_region(region, 0, size)
    plt.figure(figsize=(8, 8))
    plt.imshow(region)
    plt.show()
```



I wonder if those dark black bands are any indication of a cardioembolic stroke? Also, what are these dark black bands?
The bottom right corner of the last image (LAA type) is interesting as well- does that indicate some issue with how the clot was scanned?
I'm interested in if the center in which the image was taken could be a significant attribute in modeling...

1.4 Clean the dataset

In the STRIP.ipynb notebook, it is noted that there are several images that are blurry and could corrupt future predictions. I will remove these images from this dataset.

In [6]:

```
# remove following ids from train_df:
# b894f4_0, 6baf51_0, 7b9aaa_0, 5adc4c_0, bb06a5_0, and e26a04_0
train_df = train_df[(train_df.image_id != 'b894f4_0') &
                     (train_df.image_id != '6baf51_0') &
                     (train_df.image_id != '7b9aaa_0') &
                     (train_df.image_id != '5adc4c_0') &
                     (train_df.image_id != 'bb06a5_0') &
                     (train_df.image_id != 'e26a04_0')]

# also, reset the index of train_df
train_df = train_df.reset_index(drop=True)

# check changes
train_df
```

Out[6]:

	image_id	center_id	patient_id	image_num	label	file_path
0	006388_0	11	006388	0	CE	C:\\Users\\18016\\Downloads\\train\\006388_0.tif
1	008e5c_0	11	008e5c	0	CE	C:\\Users\\18016\\Downloads\\train\\008e5c_0.tif
2	00c058_0	11	00c058	0	LAA	C:\\Users\\18016\\Downloads\\train\\00c058_0.tif
3	01adc5_0	11	01adc5	0	LAA	C:\\Users\\18016\\Downloads\\train\\01adc5_0.tif
4	026c97_0	4	026c97	0	CE	C:\\Users\\18016\\Downloads\\train\\026c97_0.tif
...	...	...	...	...	...	...
743	fe9645_0	3	fe9645	0	CE	C:\\Users\\18016\\Downloads\\train\\fe9645_0.tif
744	fe9bec_0	4	fe9bec	0	LAA	C:\\Users\\18016\\Downloads\\train\\fe9bec_0.tif
745	ff14e0_0	6	ff14e0	0	CE	C:\\Users\\18016\\Downloads\\train\\ff14e0_0.tif
746	ffec5c_0	7	ffec5c	0	LAA	C:\\Users\\18016\\Downloads\\train\\ffec5c_0.tif
747	ffec5c_1	7	ffec5c	1	LAA	C:\\Users\\18016\\Downloads\\train\\ffec5c_1.tif

748 rows × 6 columns

Looks good. 748 items is the amount I should have.

1.5 Image transformations

Preprocessing the images because they are very large. Resizing to 512x512 pixels to try to avoid running out of memory.
Also converting images to 3 channels and converting to image array to avoiding OOM. Opening the image with OpenSlide package, which specializes in opening digital pathology Whole Slide images and .tif images.

In [7]:
```
def preprocess(image_path):
    slide = OpenSlide(image_path)     # create OpenSlide image object
    region = (0, 0)     # start at bottom left corner
    size = (10000, 10000)     # size is square 10kx10k pixels starting fro
    image = slide.read_region(region, 0, size)     # read image with param
    image = image.resize(size=(512,512)).convert('RGB')     # resizing to
    image_arr = np.array(image)    # convert image to array
    return image_arr
```

Reading in each image from the bottom left and going up and to the right by 10k pixels. This technique certainly isn't great for *every* image, but I think it's probably a decent strategy that still avoids OOM issues.

In [ ]:
```
# apply function to images

# create copy of train_df to apply changes to
tdf = train_df.copy()
image_arrays = []

for i in tqdm(tdf['file_path']):
    img_a = preprocess(i)
    image_arrays.append(img_a)

tdf['img_arr'] = image_arrays

tdf.head()
```

```
  3%|▌          | 24/748 [01:15<41:25,  3.43s/it]
```

Converted images to arrays. Easier on memory this way...

Use an ImageDataGenerator to normalize and permute the images.

In [ ]:
```
# use a simple kind of ImageDataGenerator
permutes = ImageDataGenerator(
    rescale = 1. / 255,     # normalize the data - all data points btwn 0-
    shear_range = 0.2,     # this distorts the image along an axis
    zoom_range = 0.1,     # range for random zoom
    horizontal_flip = True     # random horizontal flip
)
```

1.6 Train-test split

Split data into train and test dataframes to use for modeling. Using standard split size of 80-20 train to test % composition.

In [ ]:
```
# also make a target column because I will need int labels for modeling

# 0 - CE & 1 - LAA
tdf["target"] = tdf["label"].apply(lambda x : 0 if x=="CE" else 1)
```

In [ ]:
```
df_tt = tdf.copy()
train, test = train_test_split(df_tt, test_size=0.2, random_state=42,
                               shuffle=True)

train
```

Ensure split worked...

In [ ]:
```
plt.imshow(train.img_arr[0])
plt.show()
```

2 Modeling

2.1 Helper function for evaluation

Print out loss, RMSE, MAE, plots for these metrics, confusion matrix, and classification report.

In [21]:

```
def evaluate_model(history, model, test):
  # print loss and accuracy of the model on the test set
    test_loss, test_rmse, test_mae = history.model.evaluate(
      x=np.array(test['img_arr'].to_list()),
      y=test['target']
    )
    print(f'Test Loss: {test_loss}')
    print(f'Test RMSE: {test_rmse}')
    print(f'Test MAE: {test_mae}')

    # create plots for accuracy and loss
    fig, ax = plt.subplots(1, 2, figsize = (12,8))
    ax[0].plot(history.history['rmse'])
    ax[0].plot(history.history['val_rmse'])
    ax[0].set_title('Model RMSE')
    ax[0].set_xlabel('Epoch')
    ax[0].set_ylabel('RMSE')
    ax[0].legend(['Train', 'Test'], loc='upper left')

    ax[1].plot(history.history['loss'])
    ax[1].plot(history.history['val_loss'])
    ax[1].set_title('Model Loss')
    ax[1].set_xlabel('Epochs')
    ax[1].set_ylabel('Loss')
    ax[1].legend(['Train', 'Test'], loc='upper left')

    plt.show()

    # plot confusion matrix - create predictions for the model
    y_hat_tmp = history.model.predict(
        x=np.array(test['img_arr'].to_list())
    )

    # classify y_hat as either 0 or 1 based on if val is < or >= to 0.5
    thresh = 0.5
    y_hat = (y_hat_tmp > thresh).astype(np.int)     # cast 0 or 1 to y_hat
    y_t = test.target.astype(int)
    cm_vals = confusion_matrix(y_t, y_hat)     # get confusion matrix valu

    # plot confusion matrix values
    sns.heatmap(
      cm_vals,
      annot=True,
      cmap='Blues',
      fmt='0.5g'
    )
    plt.xlabel('Predicted Values')
    plt.ylabel('True Values')
    plt.title('Baseline Model Confusion Matrix')
    plt.show()

    # display classification report
    print(classification_report(y_t, y_hat))
```

2.2 Baseline model

Going to create simple CNN architecture for the first model.

2.2.1 Define Callbacks

In [13]:
```
# Going to use EarlyStopping Callback
es = EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=20)

# Instantiate ModelCheckpoint Callback
mc = ModelCheckpoint('best_model.h5', monitor='val_loss', mode='min',
                     save_best_only=True)
```

2.2.2 Create and fit the model

Build out simple model.

In [ ]:
```
model = models.Sequential()
input_shape = (512, 512, 3)

model.add(Conv2D(filters=32, kernel_size = (3,3), strides =2, padding = 'sa
                 activation = 'relu', input_shape = input_shape))
model.add(Conv2D(filters=64, kernel_size = (3,3), strides =2, padding = 'sa
                 activation = 'relu'))
model.add(Conv2D(filters=32, kernel_size = (3,3), strides =2, padding = 'sa
                 activation = 'relu'))
model.add(Flatten())
model.add(Dense(128, activation = 'relu'))
model.add(Dropout(0.25))

model.add(Dense(1))

model.compile(
    loss = tf.keras.losses.MeanSquaredError(),
    metrics = [tf.keras.metrics.RootMeanSquaredError(name="rmse"), 'mae'],
    optimizer = tf.keras.optimizers.Adam(1e-3)
)

model.summary()
```

In [ ]:
```
history = model.fit(
    x=np.array(train['img_arr'].to_list()),
    y=train['target'],
    batch_size=16,
    epochs=50,
    callbacks=[es, mc],
    validation_data=(np.array(test['img_arr'].to_list()), test['target'])
)
```

2.2.3 Evaluate the model

In [ ]:
```
evaluate_model(history, model, test)
```

Plots for RMSE and loss are not particularly helpful because of the extremely high values on the first model epoch, but I will not choose to correct these failures at the moment because the model did not perform well anyways... like other models so far, this model is almost always choosing CE category. It seems like no signal is detected in this model.

2.3 Dropout regularization

Goal for this model is to try some overfitting reduction strategies.

2.3.1 Create and fit the model

In [ ]:
```
model = models.Sequential()

model.add(Conv2D(32, kernel_size=(3, 3), activation='relu',
                    input_shape=(512, 512, 3)))
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))

model.add(Conv2D(32, kernel_size=(3, 3), activation='relu'))
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(2, 2))

model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))

model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))

# add dropout regularization
model.add(layers.Flatten())
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dropout(0.3))
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dropout(0.3))

model.add(layers.Dense(1))

# Compile the model
model.compile(
    loss = tf.keras.losses.MeanSquaredError(),
    metrics = [tf.keras.metrics.RootMeanSquaredError(name="rmse"), 'mae'],
    optimizer = tf.keras.optimizers.Adam(1e-3)
)

model.summary()
```

In [ ]:
```
history = model.fit(
    x=np.array(train['img_arr'].to_list()),
    y=train['target'],
    batch_size=64,
    epochs=50,
    callbacks=[es, mc],
    validation_data=(np.array(test['img_arr'].to_list()), test['target'])
)
```

2.3.2 Evaluate the model

In [ ]:
```
evaluate_model(history, model, test)
```

Model again seems to not have done anything useful.

2.4 EfficientNet model

Kaggle users for this competition have noted that EfficientNet seems to be generating some success. I will go ahead and try this model out.

Background on EfficientNet: EfficientNet is a convolutional neural network architecture and scaling method that uniformly scales all dimensions of depth/width/resolution using a compound coefficient. The scaling parameter is compound in that it is a constant ratio between the dimensions.

In [7]:
```
from tensorflow.keras.applications import EfficientNetB0     # 224x224
from tensorflow.keras.applications import EfficientNetB7     # 600x600
```

Probably will not use EffNetB7 because of OOM issues.

2.4.1 Image transformations

Need to preprocess the images as 224x224 for EfficientNetB0

In [8]:
```
def preprocess(image_path):
    slide = OpenSlide(image_path)     # create OpenSlide image object
    region = (0, 0)      # start at bottom left corner
    size = (10000, 10000)      # size is square 10kx10k pixels starting fro
    image = slide.read_region(region, 0, size)      # read image with params
    image = image.resize(size=(224,224)).convert('RGB')      # resizing to 
    image_arr = np.array(image)     # convert image to array
    return image_arr
```

Function will convert images to 3 channels and resize to 224x224 px. Then converts images to arrays to avoid OOM.

In [9]:

```python
# apply function to images

# create copy of train_df to apply changes to
tdf2 = train_df.copy()
image_arrays2 = []

for i in tqdm(train_df['file_path']):
    img_a = preprocess(i)
    image_arrays2.append(img_a)

tdf2['img_arr'] = image_arrays2

tdf2.head()
```

```
100%|██████████| 748/748 [38:25<00:00,  3.08s/it]
```

Out[9]:

	image_id	center_id	patient_id	image_num	label	file_path	i
0	006388_0	11	006388	0	CE	C:\\Users\\18016\\Downloads\\train\\006388_0.tif	
1	008e5c_0	11	008e5c	0	CE	C:\\Users\\18016\\Downloads\\train\\008e5c_0.tif	
2	00c058_0	11	00c058	0	LAA	C:\\Users\\18016\\Downloads\\train\\00c058_0.tif	
3	01adc5_0	11	01adc5	0	LAA	C:\\Users\\18016\\Downloads\\train\\01adc5_0.tif	
4	026c97_0	4	026c97	0	CE	C:\\Users\\18016\\Downloads\\train\\026c97_0.tif	

It does take quite some time to convert the images to arrays.

2.4.2 Train-test split

In [10]:
```python
# also make a target column because I will need int labels for modeling

# 0 - CE & 1 - LAA
tdf2["target"] = tdf2["label"].apply(lambda x : 0 if x=="CE" else 1)

df_tt2 = tdf2.copy()
train, test = train_test_split(df_tt2, test_size=0.2, random_state=42,
                               shuffle=True)

train
```

Out[10]:

	image_id	center_id	patient_id	image_num	label	file_pa
593	d2c18a_0	11	d2c18a	0	LAA	C:\\Users\\18016\\Downloads\\train\\d2c18a_
131	2b7304_1	3	2b7304	1	LAA	C:\\Users\\18016\\Downloads\\train\\2b7304_1
44	0d4164_0	11	0d4164	0	CE	C:\\Users\\18016\\Downloads\\train\\0d4164_
70	15de51_0	4	15de51	0	LAA	C:\\Users\\18016\\Downloads\\train\\15de51_
670	e9c181_0	10	e9c181	0	CE	C:\\Users\\18016\\Downloads\\train\\e9c181_
...	...	...	...	...	...	

	image_id	center_id	patient_id	image_num	label	file_pa
71	162cad_0	11	162cad	0	LAA	C:\\Users\\18016\\Downloads\\train\\162cad_(
106	23d2c1_1	7	23d2c1	1	CE	C:\\Users\\18016\\Downloads\\train\\23d2c1_1
270	56d177_2	7	56d177	2	CE	C:\\Users\\18016\\Downloads\\train\\56d177_2
435	91fee7_0	8	91fee7	0	CE	C:\\Users\\18016\\Downloads\\train\\91fee7_(
102	2268cf_0	11	2268cf	0	CE	C:\\Users\\18016\\Downloads\\train\\2268cf_(

598 rows × 8 columns

2.4.3 Create and fit the model

I will also try some dropout layers to try to avoid overfitting.

In [24]:

```python
efficient_net = EfficientNetB0(
    weights='imagenet',
    input_shape=(224, 224, 3),
    include_top=False,
    pooling='max',
    classes=2
)

model = models.Sequential()
model.add(efficient_net)
model.add(Dense(units=112, activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(units=224, activation = 'relu'))
model.add(Dropout(0.25))
model.add(Dense(1))

import tensorflow as tf

model.compile(
    loss = 'binary_crossentropy',
    metrics = [tf.keras.metrics.RootMeanSquaredError(name="rmse"), 'mae'],
    optimizer = tf.keras.optimizers.Adam(1e-6)
)

model.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 efficientnetb0 (Functional)  (None, 1280)             4049571   
                                                                 
 dense_12 (Dense)            (None, 112)               143472    
                                                                 
 dropout_8 (Dropout)         (None, 112)               0         
                                                                 
 dense_13 (Dense)            (None, 224)               25312     
                                                                 
 dropout_9 (Dropout)         (None, 224)               0         
                                                                 
 dense_14 (Dense)            (None, 1)                 225       
                                                                 
=================================================================
Total params: 4,218,580
Trainable params: 4,176,557
Non-trainable params: 42,023
_________________________________________________________________
```

In [25]:

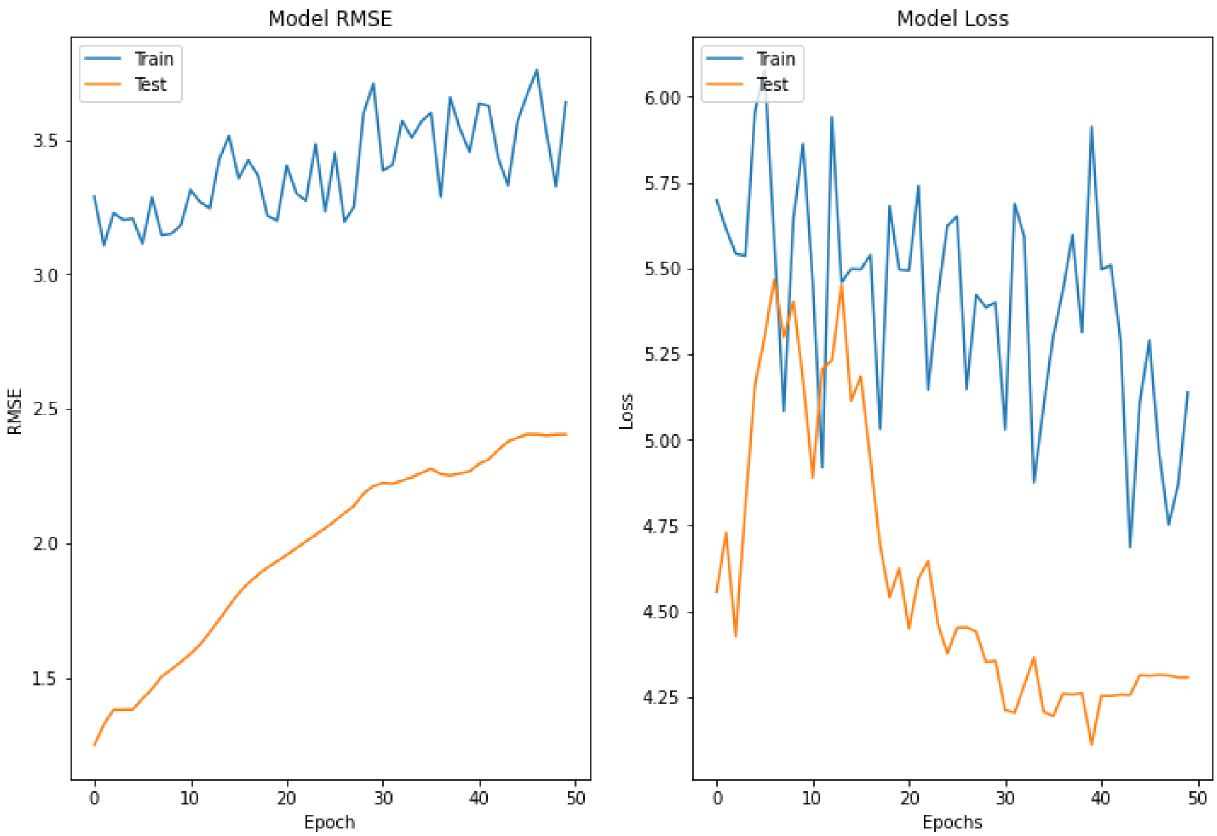
```
history = model.fit(
    x=np.array(train['img_arr'].to_list()),
    y=train['target'],
    batch_size=64,
    epochs=50,
    #callbacks=[es, mc],
    validation_data=(np.array(test['img_arr'].to_list()), test['target'])
)
```

```
Epoch 1/50
10/10 [==============================] - 57s 5s/step - loss: 5.6984 - rmse: 3.2884 - mae: 2.5250 - val_loss: 4.5564 - val_rmse: 1.2513 - val_mae: 0.9923
Epoch 2/50
10/10 [==============================] - 46s 5s/step - loss: 5.6136 - rmse: 3.1062 - mae: 2.3669 - val_loss: 4.7281 - val_rmse: 1.3281 - val_mae: 1.0521
Epoch 3/50
10/10 [==============================] - 47s 5s/step - loss: 5.5422 - rmse: 3.2280 - mae: 2.4264 - val_loss: 4.4266 - val_rmse: 1.3824 - val_mae: 1.0894
Epoch 4/50
10/10 [==============================] - 46s 5s/step - loss: 5.5358 - rmse: 3.2019 - mae: 2.4313 - val_loss: 4.8046 - val_rmse: 1.3825 - val_mae: 1.1116
Epoch 5/50
10/10 [==============================] - 46s 5s/step - loss: 5.9549 - rmse: 3.2062 - mae: 2.4897 - val_loss: 5.1581 - val_rmse: 1.3835 - val_mae: 1.1355
Epoch 6/50
10/10 [==============================] - 47s 5s/step - loss: 6.0779 - rmse: 3.1139 - mae: 2.4594 - val_loss: 5.2998 - val_rmse: 1.4236 - val_mae: 1.1717
Epoch 7/50
```

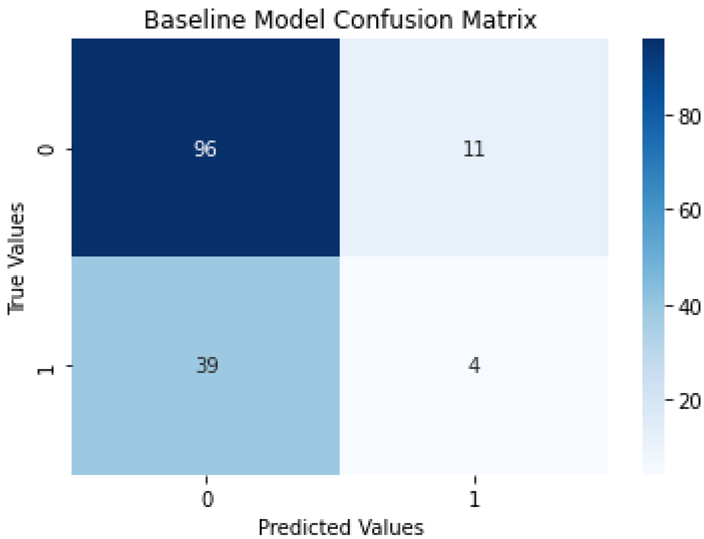
2.4.4 Evaluate the model

In [26]:
```
evaluate_model(history, model, test)
```

```
5/5 [==============================] - 3s 525ms/step - loss: 4.3069 - rmse: 2.4
051 - mae: 1.9174
Test Loss: 4.306916236877441
Test RMSE: 2.405116558074951
Test MAE: 1.9173504114151
```



```
5/5 [==============================] - 4s 525ms/step

<ipython-input-21-9e032a6d7b88>:36: DeprecationWarning: `np.int` is a deprecate
d alias for the builtin `int`. To silence this warning, use `int` by itself. Do
ing this will not modify any behavior and is safe. When replacing `np.int`, you
may wish to use e.g. `np.int64` or `np.int32` to specify the precision. If you
wish to review your current use, check the release note link for additional inf
ormation.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devd
ocs/release/1.20.0-notes.html#deprecations (https://numpy.org/devdocs/release/
1.20.0-notes.html#deprecations)
  y_hat = (y_hat_tmp > thresh).astype(np.int)     # cast 0 or 1 to y_hat values
```




```
              precision    recall  f1-score   support

           0       0.71      0.90      0.79       107
           1       0.27      0.09      0.14        43

    accuracy                           0.67       150
   macro avg       0.49      0.50      0.47       150
weighted avg       0.58      0.67      0.61       150
```

Just from CM, it would be intuited that the model is a little bit worse than random guessing. Again, I'm mainly paying attention to the loss function, but it's important to keep track of what the model is doing and where it is classifying images.

2.5 Xception Model

After speaking to my instructor (Abhineet), he recommended that I try Xception. This kind of CNN represents an "intermediate step in-between regular convolution and the depthwise separable convolution operation (a depthwise convolution followed by a pointwise convolution)." This quote is from a Francois Chollet [article (https://arxiv.org/abs/1610.02357)](https://arxiv.org/abs/1610.02357) describing this model.

In [9]:
```
# import the Xception model from Keras
from tensorflow.keras.applications.xception import Xception
```

2.5.1 Create and fit the model

In [25]:

```
xception_model = Xception(
    weights='imagenet',
    input_shape=(224, 224, 3),
    include_top=False,
    pooling='max',
    classes=2
)

model = models.Sequential()
model.add(xception_model)
model.add(Dense(units=112, activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(units=224, activation = 'relu'))
model.add(Dropout(0.25))

# sigmoid activation with binary crossentropy loss
model.add(Dense(1, activation = 'sigmoid'))

model.compile(
    loss = 'binary_crossentropy',
    metrics = [tf.keras.metrics.RootMeanSquaredError(name="rmse"), 'mae'],
    optimizer = tf.keras.optimizers.Adam(1e-6)
)

model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 xception (Functional)       (None, 2048)              20861480

 dense_9 (Dense)             (None, 112)               229488

 dropout_6 (Dropout)         (None, 112)               0

 dense_10 (Dense)            (None, 224)               25312

 dropout_7 (Dropout)         (None, 224)               0

 dense_11 (Dense)            (None, 1)                 225

=================================================================
Total params: 21,116,505
Trainable params: 21,061,977
Non-trainable params: 54,528
_________________________________________________________________
```

In [26]:

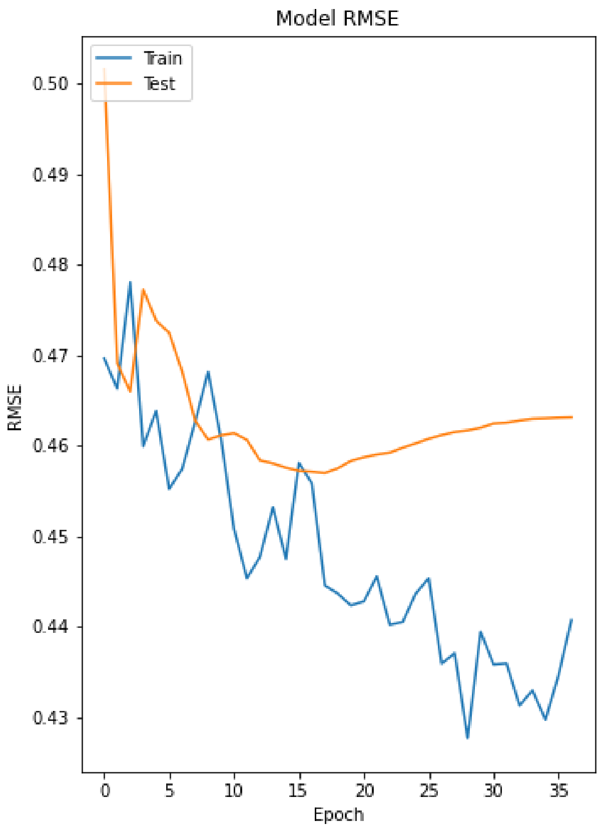
```
history = model.fit(
    x=np.array(train['img_arr'].to_list()),
    y=train['target'],
    batch_size=64,
    epochs=150,
    callbacks=[es, mc],
    validation_data=(np.array(test['img_arr'].to_list()), test['target'])
)
```

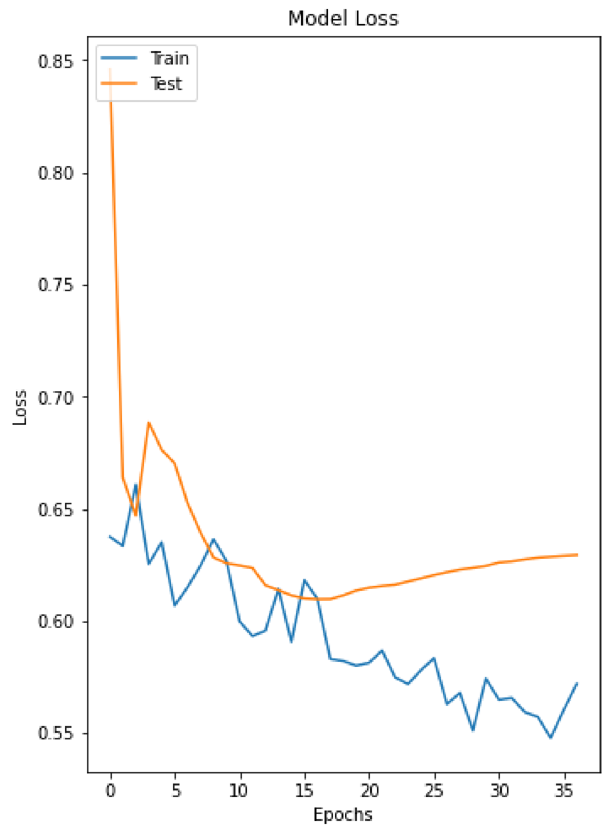
```
Epoch 1/150
10/10 [==============================] - 114s 11s/step - loss: 0.6375 - rmse: 0.4696 - mae: 0.4121 - val_loss: 0.8460 - val_rmse: 0.5016 - val_mae: 0.3213
Epoch 2/150
10/10 [==============================] - 102s 10s/step - loss: 0.6335 - rmse: 0.4663 - mae: 0.4102 - val_loss: 0.6640 - val_rmse: 0.4691 - val_mae: 0.3546
Epoch 3/150
10/10 [==============================] - 101s 10s/step - loss: 0.6608 - rmse: 0.4780 - mae: 0.4233 - val_loss: 0.6470 - val_rmse: 0.4659 - val_mae: 0.3671
Epoch 4/150
10/10 [==============================] - 100s 10s/step - loss: 0.6254 - rmse: 0.4599 - mae: 0.4043 - val_loss: 0.6885 - val_rmse: 0.4772 - val_mae: 0.3420
Epoch 5/150
10/10 [==============================] - 99s 10s/step - loss: 0.6351 - rmse: 0.4638 - mae: 0.4103 - val_loss: 0.6763 - val_rmse: 0.4738 - val_mae: 0.3436
Epoch 6/150
10/10 [==============================] - 101s 10s/step - loss: 0.6068 - rmse: 0.4552 - mae: 0.3998 - val_loss: 0.6703 - val_rmse: 0.4724 - val_mae: 0.3551
Epoch 7/150
```

2.5.2 Evaluate the model

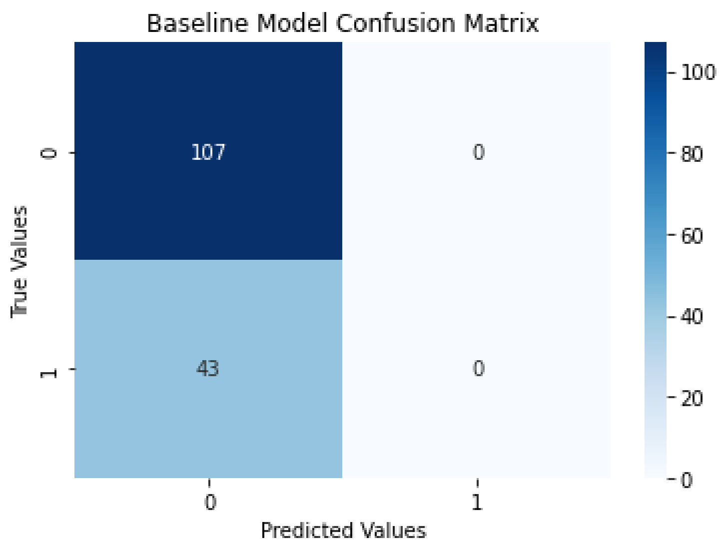
In [27]:
```
1 evaluate_model(history, model, test)
```

```
5/5 [==============================] - 6s 1s/step - loss: 0.6294 - rmse: 0.4631
- mae: 0.3999
Test Loss: 0.6293601989746094
Test RMSE: 0.46309494972229004
Test MAE: 0.3998658359050751
```





```
5/5 [==============================] - 6s 1s/step

<ipython-input-10-9e032a6d7b88>:36: DeprecationWarning: `np.int` is a deprecate
d alias for the builtin `int`. To silence this warning, use `int` by itself. Do
ing this will not modify any behavior and is safe. When replacing `np.int`, you
may wish to use e.g. `np.int64` or `np.int32` to specify the precision. If you
wish to review your current use, check the release note link for additional inf
ormation.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devd
ocs/release/1.20.0-notes.html#deprecations (https://numpy.org/devdocs/release/
1.20.0-notes.html#deprecations)
  y_hat = (y_hat_tmp > thresh).astype(np.int)     # cast 0 or 1 to y_hat values
```




```
              precision    recall  f1-score   support

           0       0.71      1.00      0.83       107
           1       0.00      0.00      0.00        43

    accuracy                           0.71       150
   macro avg       0.36      0.50      0.42       150
weighted avg       0.51      0.71      0.59       150


C:\Users\18016\anaconda3\envs\learn-env\lib\site-packages\sklearn\metrics\_clas
sification.py:1221: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_division
` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

The loss is better than baseline, but the model is just predicting CE category for every image. The bottom or valley of the loss and RMSE is very clear from the graphs.

3 Import png image dataset

I think this dataset will be much more manageable to work with, and hopefully higher resolution of each image will be allowed in model iterations involving this dataset. The goal is for higher resolution to capture features within the data.

In [3]:

```
# load in the dataset
train_path = r"C:\\Users\\18016\\Desktop\\train_images_cleaned\\"
train_df["file_path"] = train_df["image_id"].apply(lambda x: train_path + x
train_df.head()
```

Out[3]:

	image_id	center_id	patient_id	image_num	label	file_path
0	006388_0	11	006388	0	CE	C:\\Users\\18016\\Desktop\\train_images_cleane...
1	008e5c_0	11	008e5c	0	CE	C:\\Users\\18016\\Desktop\\train_images_cleane...
2	00c058_0	11	00c058	0	LAA	C:\\Users\\18016\\Desktop\\train_images_cleane...
3	01adc5_0	11	01adc5	0	LAA	C:\\Users\\18016\\Desktop\\train_images_cleane...
4	026c97_0	4	026c97	0	CE	C:\\Users\\18016\\Desktop\\train_images_cleane...

3.1 Clean the dataset

In [5]:

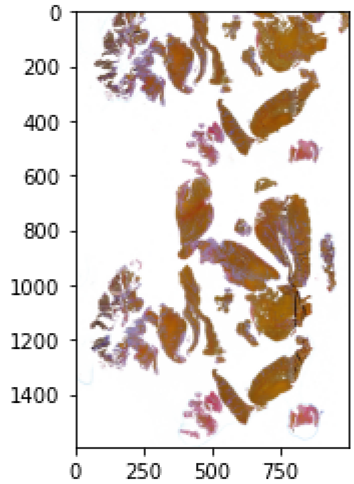
```
# follow same process as in 1.3

# remove following ids from train_df:
# b894f4_0, 6baf51_0, 7b9aaa_0, 5adc4c_0, bb06a5_0, and e26a04_0
train_df = train_df[(train_df.image_id != 'b894f4_0') &
                     (train_df.image_id != '6baf51_0') &
                     (train_df.image_id != '7b9aaa_0') &
                     (train_df.image_id != '5adc4c_0') &
                     (train_df.image_id != 'bb06a5_0') &
                     (train_df.image_id != 'e26a04_0')]

# also, reset the index of train_df
train_df = train_df.reset_index(drop=True)
```

These images are removed due to issues with them being distorted, blurry, or having some other issue. These were mainly identified by Kaggle users.

3.2 Preview an image

In [7]:
```
img = Image.open(train_df.file_path[0])
plt.imshow(img)
```

Out[7]: <matplotlib.image.AxesImage at 0x22c1539e790>



3.3 Preprocess images

Normalize and permute with ImageDataGenerator, perform train-test-split, and fit datagenerator to train and test set.

In [8]:
```
# use ImageDataGenerator
permutes = ImageDataGenerator(
    rescale = 1. / 255,     # normalize values btwn 0-1
    shear_range = 0.2,     # this distorts the image along an axis
    zoom_range = 0.2,     # range for random zoom
    horizontal_flip = True     # random horizontal flip
)

# 80-20 standard split
df_tt = train_df.copy()
train, test = train_test_split(df_tt, test_size=0.2, random_state=42,
                               shuffle=True)


# fit the image modifier/permuter
# use target size of 299x299 pixels. That is the default input image size
# Xception. Maybe it will perform better with this size, but I imagine that
# larger (more resolute) images would perform better in general.
train_gen = permutes.flow_from_dataframe(dataframe=train, x_col='file_path
                                         y_col='label', target_size=(299,2
                                         class_mode='binary', batch_size=1
                                         seed=42)

test_gen = permutes.flow_from_dataframe(dataframe=test, x_col='file_path',
                                         y_col='label', target_size=(299,2
                                         class_mode='binary', batch_size=1
                                         seed=42)
```

```
Found 598 validated image filenames belonging to 2 classes.
Found 150 validated image filenames belonging to 2 classes.
```

Image size is 299x299 because Xception defaults to this size. I want to try this size... It's so specific that maybe there is some optimization for it, but I imagine more resolute images work better in general.

3.4 Xception Model

3.4.1 Create and fit model

Use the default input size of 299x299 pixels for Xception.

In [12]:

```
xception_model = Xception(
    weights='imagenet',
    input_shape=(299, 299, 3),
    include_top=False,
    pooling='max',
    classes=2
)

# using dropout of 0.5 in hopes of decreasing overfitting.

model = models.Sequential()
model.add(xception_model)
model.add(Dense(units=229, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(units=458, activation = 'relu'))
model.add(Dropout(0.5))

# sigmoid activation with binary crossentropy loss
model.add(Dense(1, activation = 'sigmoid'))

model.compile(
    loss = 'binary_crossentropy',
    metrics = [tf.keras.metrics.RootMeanSquaredError(name="rmse"), 'mae'],
    optimizer = tf.keras.optimizers.Adam(1e-6)
)

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 xception (Functional)       (None, 2048)              20861480  
                                                                 
 dense (Dense)               (None, 229)               469221    
                                                                 
 dropout (Dropout)           (None, 229)               0         
                                                                 
 dense_1 (Dense)             (None, 458)               105340    
                                                                 
 dropout_1 (Dropout)         (None, 458)               0         
                                                                 
 dense_2 (Dense)             (None, 1)                 459       
                                                                 
=================================================================
Total params: 21,436,500
Trainable params: 21,381,972
Non-trainable params: 54,528
_________________________________________________________________
```

In [13]:

```
history = model.fit(
    x=train_gen,
    steps_per_epoch=train_gen.n//train_gen.batch_size,
    validation_data=test_gen,
    validation_steps=test_gen.n//test_gen.batch_size,
    epochs=50,
    callbacks=[es, mc]
)
```

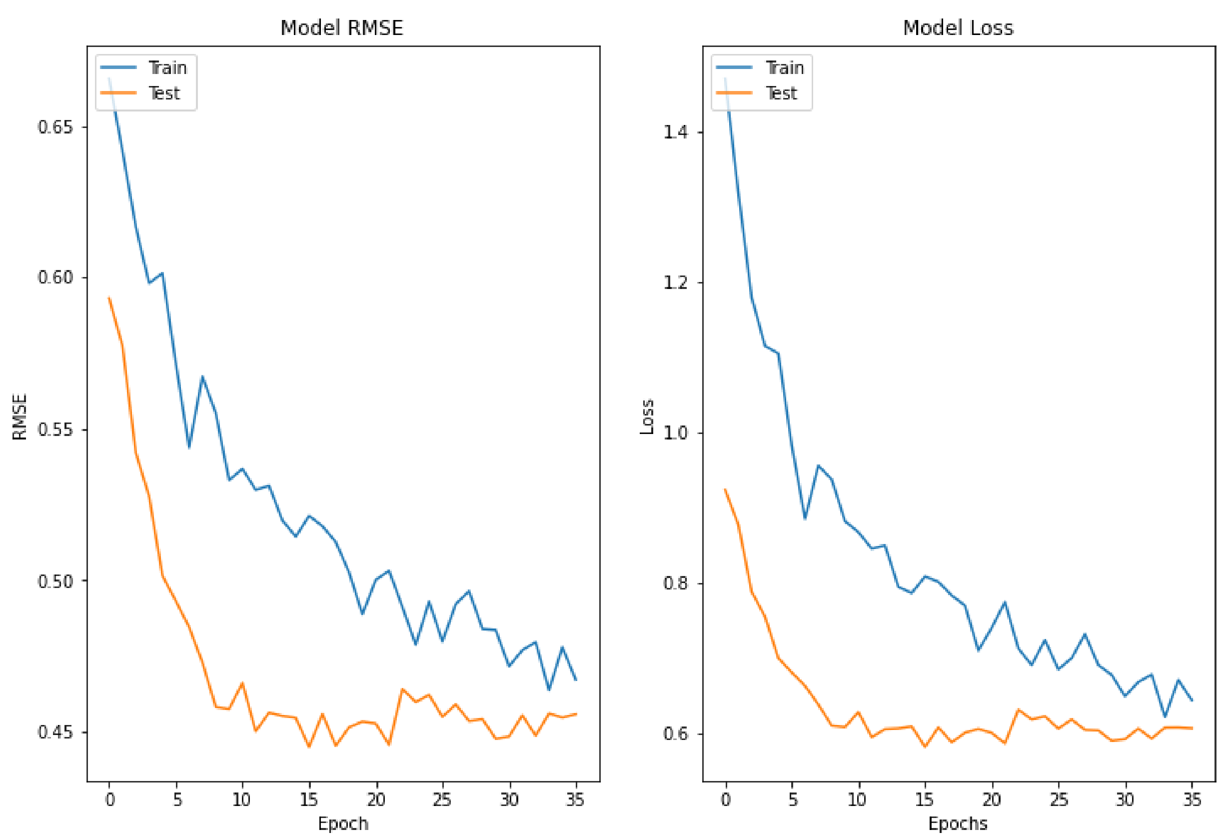
```
Epoch 1/50
37/37 [==============================] - 143s 4s/step - loss: 1.4697 - rmse:
0.6656 - mae: 0.5798 - val_loss: 0.9234 - val_rmse: 0.5931 - val_mae: 0.5656
Epoch 2/50
37/37 [==============================] - 137s 4s/step - loss: 1.3186 - rmse:
0.6418 - mae: 0.5534 - val_loss: 0.8771 - val_rmse: 0.5774 - val_mae: 0.5558
Epoch 3/50
37/37 [==============================] - 139s 4s/step - loss: 1.1789 - rmse:
0.6168 - mae: 0.5296 - val_loss: 0.7878 - val_rmse: 0.5421 - val_mae: 0.5239
Epoch 4/50
37/37 [==============================] - 137s 4s/step - loss: 1.1146 - rmse:
0.5980 - mae: 0.5101 - val_loss: 0.7547 - val_rmse: 0.5276 - val_mae: 0.5116
Epoch 5/50
37/37 [==============================] - 139s 4s/step - loss: 1.1044 - rmse:
0.6014 - mae: 0.5184 - val_loss: 0.6996 - val_rmse: 0.5015 - val_mae: 0.4836
Epoch 6/50
37/37 [==============================] - 139s 4s/step - loss: 0.9832 - rmse:
0.5717 - mae: 0.4884 - val_loss: 0.6807 - val_rmse: 0.4931 - val_mae: 0.4765
Epoch 7/50
```

3.4.2 Evaluate the model

In [14]:

```
test_loss, test_rmse, test_mae = history.model.evaluate(test_gen)
print(f'Test Loss: {test_loss}')
print(f'Test RMSE: {test_rmse}')
print(f'Test MAE: {test_mae}')

# create plots for accuracy and loss
fig, ax = plt.subplots(1, 2, figsize = (12,8))
ax[0].plot(history.history['rmse'])
ax[0].plot(history.history['val_rmse'])
ax[0].set_title('Model RMSE')
ax[0].set_xlabel('Epoch')
ax[0].set_ylabel('RMSE')
ax[0].legend(['Train', 'Test'], loc='upper left')

ax[1].plot(history.history['loss'])
ax[1].plot(history.history['val_loss'])
ax[1].set_title('Model Loss')
ax[1].set_xlabel('Epochs')
ax[1].set_ylabel('Loss')
ax[1].legend(['Train', 'Test'], loc='upper left')

plt.show()
```

```
10/10 [==============================] - 9s 869ms/step - loss: 0.6038 - rmse:
0.4541 - mae: 0.3998
Test Loss: 0.6037670969963074
Test RMSE: 0.45410773158073425
Test MAE: 0.3997587561607361
```

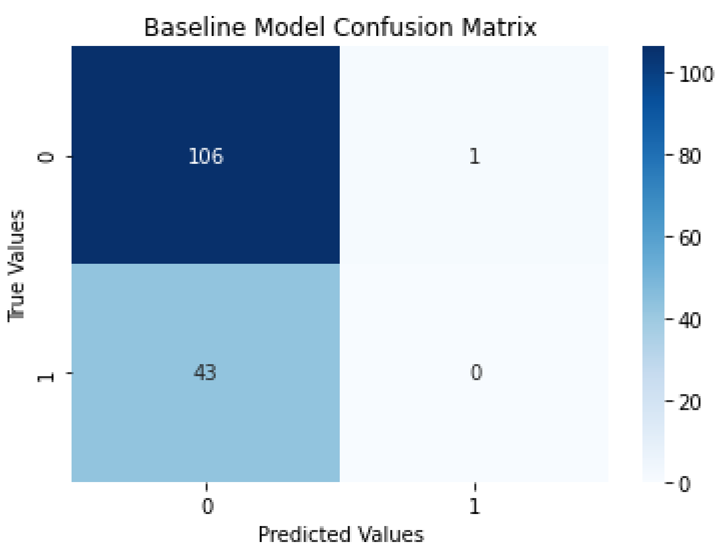


In [15]:
```
# need integer labels for more evaluation
df_test_tmp = test.copy()
df_test_tmp.loc[df_test_tmp['label'] == 'CE', 'label'] = 0     # CE is now
df_test_tmp.loc[df_test_tmp['label'] == 'LAA', 'label'] = 1     # LAA is no
```

In [16]:

```python
# Create predictions for the model
y_hat_tmp = history.model.predict(test_gen)

# classify y_hat as either 0 or 1 based on if val is < or >= to 0.5
thresh = 0.5
y_hat = (y_hat_tmp > thresh).astype(np.int)     # cast 0 or 1 to y_hat val

y_t = df_test_tmp.label.astype(int)

cm_vals = confusion_matrix(y_t, y_hat)     # get confusion matrix values

# plot confusion matrix values
sns.heatmap(
    cm_vals,
    annot=True,
    cmap='Blues',
    fmt='0.5g'
)

plt.xlabel('Predicted Values')
plt.ylabel('True Values')
plt.title('Baseline Model Confusion Matrix')
plt.show()
```

```
10/10 [==============================] - 10s 877ms/step

<ipython-input-16-c4d092d549eb>:6: DeprecationWarning: `np.int` is a deprecated
alias for the builtin `int`. To silence this warning, use `int` by itself. Doin
g this will not modify any behavior and is safe. When replacing `np.int`, you m
ay wish to use e.g. `np.int64` or `np.int32` to specify the precision. If you w
ish to review your current use, check the release note link for additional info
rmation.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devd
ocs/release/1.20.0-notes.html#deprecations (https://numpy.org/devdocs/release/
1.20.0-notes.html#deprecations)
  y_hat = (y_hat_tmp > thresh).astype(np.int)     # cast 0 or 1 to y_hat values
```



Unfortunately, this model is guessing CE category almost every time it makes a prediction.

Notice the lower loss here. Lowest loss score thus far.

3.5 Xception Model retry

Maybe higher resolution will allow for better predictions. I am going to try to double the resolution used in the previous model from 299x299 to 598x598.

In [17]:

```
train_gen = permutes.flow_from_dataframe(dataframe=train, x_col='file_path
                                          y_col='label', target_size=(598,59
                                          class_mode='binary', batch_size=1(
                                          seed=42)

test_gen = permutes.flow_from_dataframe(dataframe=test, x_col='file_path',
                                          y_col='label', target_size=(598,59
                                          class_mode='binary', batch_size=1(
                                          seed=42)
```

```
Found 598 validated image filenames belonging to 2 classes.
Found 150 validated image filenames belonging to 2 classes.
```

3.5.1 Create and fit model

In [18]:
```
xception_model = Xception(
    weights='imagenet',
    input_shape=(598, 598, 3),
    include_top=False,
    pooling='max',
    classes=2
)

# using dropout of 0.5 in hopes of decreasing overfitting.

model = models.Sequential()
model.add(xception_model)
model.add(Dense(units=299, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(units=598, activation = 'relu'))
model.add(Dropout(0.5))

# sigmoid activation with binary crossentropy loss
model.add(Dense(1, activation = 'sigmoid'))

model.compile(
    loss = 'binary_crossentropy',
    metrics = [tf.keras.metrics.RootMeanSquaredError(name="rmse"), 'mae'],
    optimizer = tf.keras.optimizers.Adam(1e-6)
)

model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 xception (Functional)       (None, 2048)              20861480  
                                                                 
 dense_3 (Dense)             (None, 299)               612651    
                                                                 
 dropout_2 (Dropout)         (None, 299)               0         
                                                                 
 dense_4 (Dense)             (None, 598)               179400    
                                                                 
 dropout_3 (Dropout)         (None, 598)               0         
                                                                 
 dense_5 (Dense)             (None, 1)                 599       
                                                                 
=================================================================
Total params: 21,654,130
Trainable params: 21,599,602
Non-trainable params: 54,528
_________________________________________________________________
```

In [20]:

```
history = model.fit(
    x=train_gen,
    steps_per_epoch=train_gen.n//train_gen.batch_size,
    validation_data=test_gen,
    validation_steps=test_gen.n//test_gen.batch_size,
    epochs=50,
    callbacks=[es, mc]
)
```

```
Epoch 1/50
37/37 [==============================] - 612s 16s/step - loss: 1.0309 - rmse:
0.5600 - mae: 0.4393 - val_loss: 0.6205 - val_rmse: 0.4597 - val_mae: 0.3930
Epoch 2/50
37/37 [==============================] - 528s 14s/step - loss: 0.9878 - rmse:
0.5541 - mae: 0.4348 - val_loss: 0.6196 - val_rmse: 0.4579 - val_mae: 0.3790
Epoch 3/50
37/37 [==============================] - 521s 14s/step - loss: 1.1258 - rmse:
0.5720 - mae: 0.4500 - val_loss: 0.6255 - val_rmse: 0.4598 - val_mae: 0.3652
Epoch 4/50
37/37 [==============================] - 518s 14s/step - loss: 0.9677 - rmse:
0.5411 - mae: 0.4190 - val_loss: 0.6160 - val_rmse: 0.4565 - val_mae: 0.3502
Epoch 5/50
37/37 [==============================] - 521s 14s/step - loss: 0.8985 - rmse:
0.5249 - mae: 0.4117 - val_loss: 0.6667 - val_rmse: 0.4699 - val_mae: 0.3638
Epoch 6/50
37/37 [==============================] - 529s 14s/step - loss: 0.9132 - rmse:
0.5329 - mae: 0.4125 - val_loss: 0.6556 - val_rmse: 0.4645 - val_mae: 0.3535
Epoch 7/50
37/37 [==============================] - 522s 14s/step - loss: 0.8740 - rmse:
0.5230 - mae: 0.4087 - val_loss: 0.6631 - val_rmse: 0.4720 - val_mae: 0.3606
Epoch 8/50
37/37 [==============================] - 521s 14s/step - loss: 0.9306 - rmse:
0.5287 - mae: 0.4132 - val_loss: 0.6737 - val_rmse: 0.4733 - val_mae: 0.3592
Epoch 9/50
37/37 [==============================] - 524s 14s/step - loss: 0.8649 - rmse:
0.5180 - mae: 0.4017 - val_loss: 0.6432 - val_rmse: 0.4661 - val_mae: 0.3593
Epoch 10/50
37/37 [==============================] - 523s 14s/step - loss: 0.8810 - rmse:
0.5196 - mae: 0.4032 - val_loss: 0.6697 - val_rmse: 0.4741 - val_mae: 0.3647
Epoch 11/50
37/37 [==============================] - 535s 14s/step - loss: 0.8995 - rmse:
0.5239 - mae: 0.4073 - val_loss: 0.6592 - val_rmse: 0.4689 - val_mae: 0.3661
Epoch 12/50
37/37 [==============================] - 522s 14s/step - loss: 0.8118 - rmse:
0.5041 - mae: 0.3981 - val_loss: 0.6659 - val_rmse: 0.4744 - val_mae: 0.3679
Epoch 13/50
37/37 [==============================] - 520s 14s/step - loss: 0.7760 - rmse:
0.5027 - mae: 0.4059 - val_loss: 0.6364 - val_rmse: 0.4621 - val_mae: 0.3613
Epoch 14/50
37/37 [==============================] - 521s 14s/step - loss: 0.8235 - rmse:
0.5136 - mae: 0.4189 - val_loss: 0.6492 - val_rmse: 0.4687 - val_mae: 0.3703
Epoch 15/50
37/37 [==============================] - 525s 14s/step - loss: 0.7659 - rmse:
0.4941 - mae: 0.3980 - val_loss: 0.6477 - val_rmse: 0.4678 - val_mae: 0.3669
Epoch 16/50
37/37 [==============================] - 573s 16s/step - loss: 0.7541 - rmse:
```

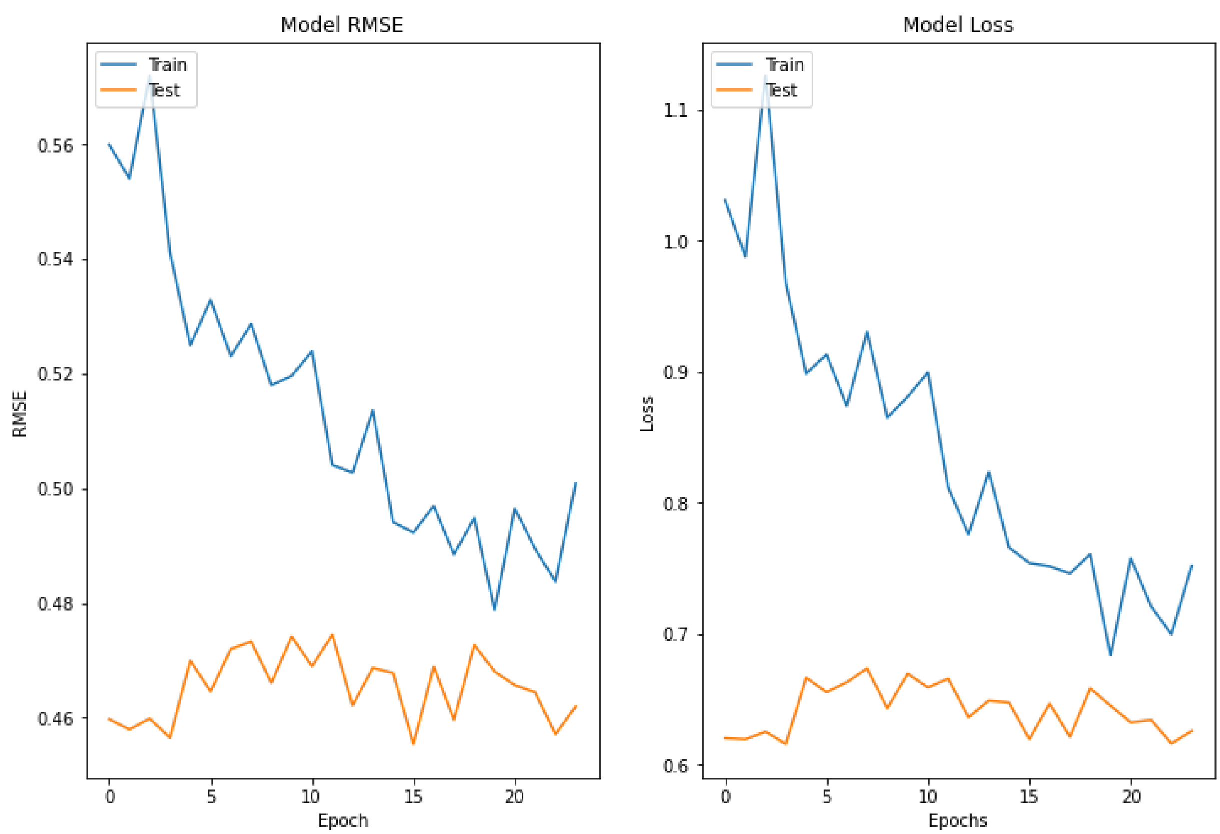
```
0.4923 - mae: 0.3903 - val_loss: 0.6197 - val_rmse: 0.4554 - val_mae: 0.3563
Epoch 17/50
37/37 [==============================] - 597s 16s/step - loss: 0.7516 - rmse:
0.4969 - mae: 0.4033 - val_loss: 0.6469 - val_rmse: 0.4688 - val_mae: 0.3715
Epoch 18/50
37/37 [==============================] - 601s 16s/step - loss: 0.7461 - rmse:
0.4885 - mae: 0.3864 - val_loss: 0.6215 - val_rmse: 0.4596 - val_mae: 0.3701
Epoch 19/50
37/37 [==============================] - 534s 14s/step - loss: 0.7608 - rmse:
0.4948 - mae: 0.4077 - val_loss: 0.6585 - val_rmse: 0.4727 - val_mae: 0.3777
Epoch 20/50
37/37 [==============================] - 535s 14s/step - loss: 0.6838 - rmse:
0.4788 - mae: 0.3870 - val_loss: 0.6453 - val_rmse: 0.4680 - val_mae: 0.3814
Epoch 21/50
37/37 [==============================] - 529s 14s/step - loss: 0.7577 - rmse:
0.4965 - mae: 0.4064 - val_loss: 0.6325 - val_rmse: 0.4656 - val_mae: 0.3823
Epoch 22/50
37/37 [==============================] - 523s 14s/step - loss: 0.7209 - rmse:
0.4894 - mae: 0.4052 - val_loss: 0.6344 - val_rmse: 0.4644 - val_mae: 0.3819
Epoch 23/50
37/37 [==============================] - 526s 14s/step - loss: 0.6997 - rmse:
0.4837 - mae: 0.4034 - val_loss: 0.6164 - val_rmse: 0.4571 - val_mae: 0.3778
Epoch 24/50
37/37 [==============================] - 528s 14s/step - loss: 0.7519 - rmse:
0.5009 - mae: 0.4160 - val_loss: 0.6260 - val_rmse: 0.4619 - val_mae: 0.3822
Epoch 24: early stopping
```

3.5.2 Evaluate the model

In [21]:

```
test_loss, test_rmse, test_mae = history.model.evaluate(test_gen)
print(f'Test Loss: {test_loss}')
print(f'Test RMSE: {test_rmse}')
print(f'Test MAE: {test_mae}')

# create plots for accuracy and loss
fig, ax = plt.subplots(1, 2, figsize = (12,8))
ax[0].plot(history.history['rmse'])
ax[0].plot(history.history['val_rmse'])
ax[0].set_title('Model RMSE')
ax[0].set_xlabel('Epoch')
ax[0].set_ylabel('RMSE')
ax[0].legend(['Train', 'Test'], loc='upper left')

ax[1].plot(history.history['loss'])
ax[1].plot(history.history['val_loss'])
ax[1].set_title('Model Loss')
ax[1].set_xlabel('Epochs')
ax[1].set_ylabel('Loss')
ax[1].legend(['Train', 'Test'], loc='upper left')

plt.show()
```

```
10/10 [==============================] - 24s 2s/step - loss: 0.6063 - rmse: 0.4
531 - mae: 0.3778
Test Loss: 0.6063445806503296
Test RMSE: 0.4530891180038452
Test MAE: 0.3777797818183899
```

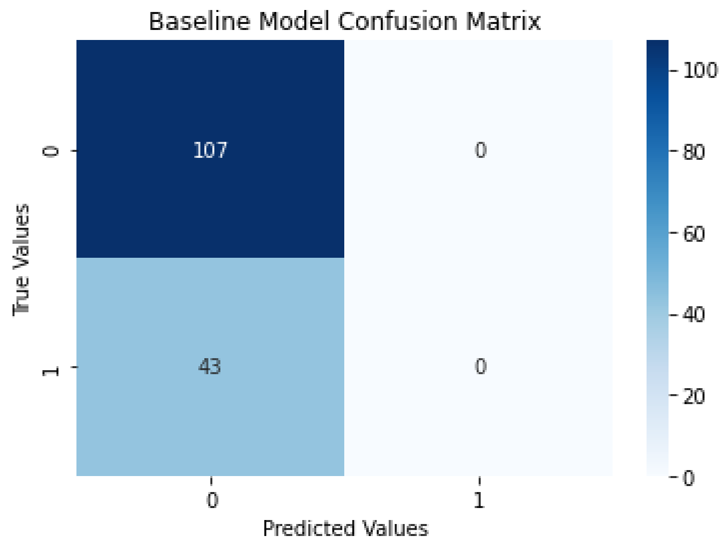


The loss and RMSE of the test function is flat throughout the duration but looks like maybe they would eventually converge. The loss is just a bit more than the previous Xception model.

In [25]:

```
1  # need integer labels for more evaluation
2  df_test_tmp = test.copy()
3  df_test_tmp.loc[df_test_tmp['label'] == 'CE', 'label'] = 0     # CE is now
4  df_test_tmp.loc[df_test_tmp['label'] == 'LAA', 'label'] = 1     # LAA is no
5  
6  # Create predictions for the model
7  y_hat_tmp = history.model.predict(test_gen)
8  
9  # classify y_hat as either 0 or 1 based on if val is < or >= to 0.5
10 thresh = 0.5
11 y_hat = (y_hat_tmp > thresh).astype(np.int)     # cast 0 or 1 to y_hat valu
12 
13 y_t = df_test_tmp.label.astype(int)
14 
15 cm_vals = confusion_matrix(y_t, y_hat)     # get confusion matrix values
16 
17 # plot confusion matrix values
18 sns.heatmap(
19     cm_vals,
20     annot=True,
21     cmap='Blues',
22     fmt='0.5g'
23 )
24 
25 plt.xlabel('Predicted Values')
26 plt.ylabel('True Values')
27 plt.title('Baseline Model Confusion Matrix')
28 plt.show()
```

```
10/10 [==============================] - 23s 2s/step

<ipython-input-25-14eb97735682>:11: DeprecationWarning: `np.int` is a deprecate
d alias for the builtin `int`. To silence this warning, use `int` by itself. Do
ing this will not modify any behavior and is safe. When replacing `np.int`, you
may wish to use e.g. `np.int64` or `np.int32` to specify the precision. If you
wish to review your current use, check the release note link for additional inf
ormation.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devd
ocs/release/1.20.0-notes.html#deprecations (https://numpy.org/devdocs/release/
1.20.0-notes.html#deprecations)
  y_hat = (y_hat_tmp > thresh).astype(np.int)     # cast 0 or 1 to y_hat values
```



Again, the model is predicting that each image represents the CE category.

4 Modeling Conclusions

Ultimately the results here are very disappointing. This dataset is exceptionally hard and it's impossible to not lose most of the image's resolution when preprocessing the image because it is so easy to run into OOM issues.

Most of the models seem to essentially be guessing CE category for every validation image. I highly doubt there is any sort feature detection involved in any of these images (i.e. models do not detect any pattern in particular differentiating the two categories).

One of the Xception models performed slightly better in terms of loss than the baseline model. It might be *slightly* more confident in guessing the images when they are CE than the baseline, but it should be assumed that both models are guessing CE for each image with roughly the same confidence. It should be assumed there is not a difference between the performance of these two models especially considering there are no indications of a significant difference in any metric - even .06 or so difference in loss does not indicate significance. This difference could be attributed to randomness in how confident the models are for each individual image in the test set.

4.1 Actionable recommendations to the stakeholder

To reiterate clarify recommendations for the stakeholder, I am including the "Actionable recommendations" section from the Google Colab notebook here as well:
To create a more effective predictive model, a diagnostic tool should be created that will automatically read in new data and automatically make predictions that will help physicians with a diagnosis. This diagnostic tool should take advantage of new Whole Slide images from each patient, and it should also incorporate other data such as mass spectrometry readings of protein content from the blood clot and additional biomarkers from each patient such as whether or not the

patient has a history of cardioembolic or large artery atherosclerosis strokes in their family. With the incorporation of new data, the model will continue learning and refining predictions to allow for better predictions.