Histopathologic Cancer Detection

October 11, 2022

1 Problem Description

- Cancer accounted for nearly 10 million deaths in 2020. Or, put another way, 1 in every 6 deaths was caused by cancer (WHO, 2022).
- Even though we don't have a cure for cancer, early detection of it will go a long way in preventing many deaths (WHO, 2022).
- The dataset for this challenge is sourced from a modified version of PCam benchmark dataset (Kaggle, 2018).
- The original dataset contains hundreds of thousands of images of pathology scans that have been labelled as cancerous or non-cancerous.
- The Kaggle dataset removed duplicates from the original dataset to make it easier for people to train ML models.
- **Problem**: Create a deep learning model to identify metastatic cancer in pathology scans.

Data Description

- The dataset consists of images in 2 folders: `training` & `test`
  - Training set contains 220,025 images
  - Test set contains 57,458 images
- Each image is 96 by 96 pixes
- Each image contains 3 color channels: Red, Green & Blue
- Authors have tried to put the *cancerous tissue* in the center of each image. But it wasn't possible to do for every image.

References

- Ehteshami Bejnordi, et al. (2017). Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in women with breast cancer. JAMA, 318(22), 2199. https://doi.org/10.1001/jama.2017.14585
- Histopathologic Cancer detection. Kaggle. (2018). Retrieved October 10, 2022, from https://www.kaggle.com/competitions/histopathologic-cancer-detection/overview
- Veeling, B. S., Linmans, J., Winkens, J., Cohen, T., & Welling, M. (2018). Rotation equivariant CNNS for digital pathology. Medical Image Computing and Computer Assisted Intervention – MICCAI 2018, 210–218. https://doi.org/10.1007/978-3-030-00934-2_24
- WHO. (2022, February 3). Cancer. World Health Organization. Retrieved October 10, 2022, from https://www.who.int/news-room/fact-sheets/detail/cancer

2 Exploratory Data Analysis

The data has already been split into training & test sets by the competition organizers.

[322]:
```
import numpy as np
import pandas as pd
import os
import random

import matplotlib.pyplot as plt
import matplotlib.patches as patches
from PIL import Image

from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score

import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import RandomFlip, RandomZoom, RandomRotation
from tensorflow.keras.layers import Conv2D, MaxPooling2D, AveragePooling2D,␣
↪Input
from tensorflow.keras.layers import Dense, Flatten, Dropout, Activation
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import BatchNormalization
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau,␣
↪ModelCheckpoint

import warnings
warnings.simplefilter("ignore", category=DeprecationWarning)
```

[323]:
```
tf.__version__
```

[323]: '2.10.0'

[324]:
```
test_path = './histopathologic-cancer-detection/test/'
train_path = './histopathologic-cancer-detection/train/'
train_data = pd.read_csv('./histopathologic-cancer-detection/train_labels.csv')
```

[325]:
```
train_data.shape
```

[325]: (220025, 2)

[326]:
```
train_data.head()
```

[326]:

	id	label
0	f38a6374c348f90b587e046aac6079959adf3835	0
1	c18f2d887b7ae4f6742ee445113fa1aef383ed77	1
2	755db6279dae599ebb4d39a9123cce439965282d	0
3	bc3f0c64fb968ff4a8bd33af6971ecae77c75e08	0
4	068aba587a4950175d04c680d38943fd488d6a9d	0

`train_data` contains the filenames in the `id` column and the correct label for them. The `label` is marked 1 if tumor tissue was found, 0 otherwise.

[327]:
```
print(f'training: {len(os.listdir(train_path))}')
print(f'test: {len(os.listdir(test_path))}')
```

```
training: 220025
test: 57458
```

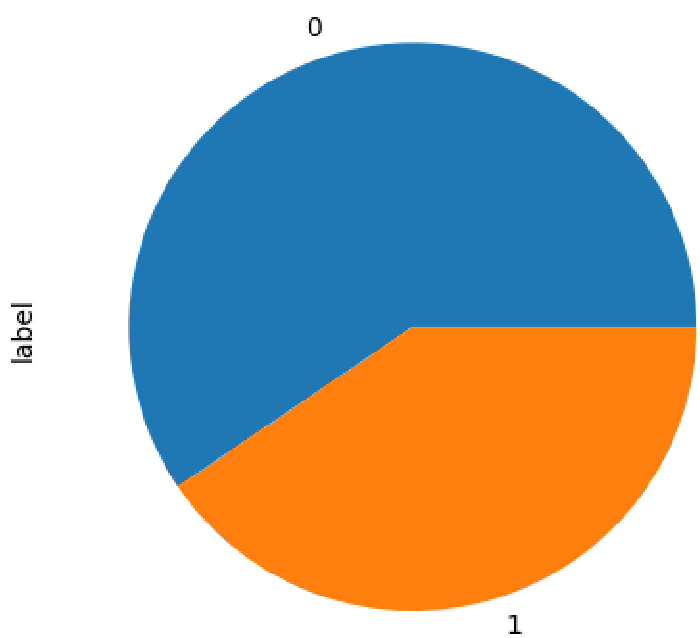
- There are 220025 images in the `training` dataset and 57458 images in the `test` dataset.

[328]:
```
train_data['label'].value_counts()
```

[328]:
```
0    130908
1     89117
Name: label, dtype: int64
```

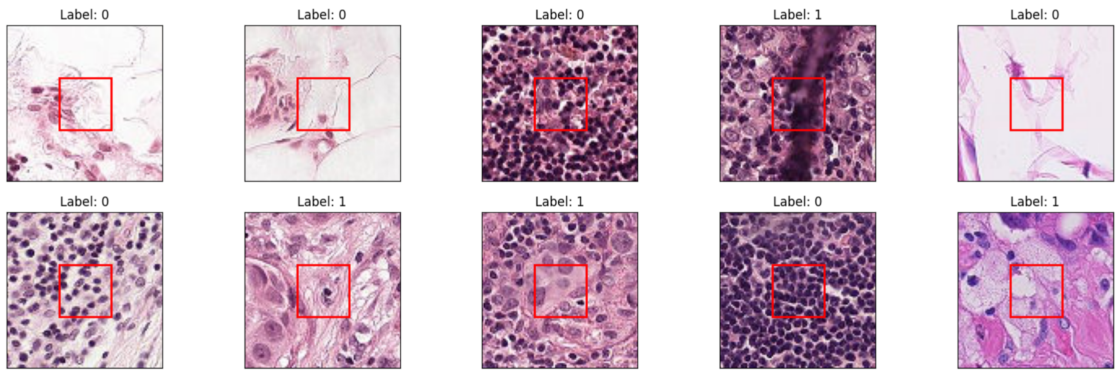
[329]:
```
train_data['label'].value_counts().plot(kind='pie')
```

[329]:
```
<AxesSubplot: ylabel='label'>
```



- The class distribution in the training dataset is *slightly* uneven.
- For now, I'll be skipping the steps to rebalance the dataset. But based on the results of the CNN, I might re-visit this decision.

[203]:
```
fig = plt.figure(figsize=(20, 6))

for idx, img in enumerate(np.random.choice(os.listdir(train_path), 10)):
    ax = fig.add_subplot(2, 10//2, idx+1, xticks=[], yticks=[])
    im = Image.open(f"{train_path}" + img)
    plt.imshow(im)
    lab = train_data.loc[train_data['id'] == img.split('.')[0], 'label'].
↪values[0]
    ax.set_title(f'Label: {lab}')
    box = patches.Rectangle((32,32),32,32, linewidth=2,␣
↪edgecolor='r',facecolor='none', linestyle='-')
    ax.add_patch(box)
```



- With a quick visual analysis, I can't distinctly differentiate the scans that have a tumor (label = 1) from those that don't. But then again, I am not a radiologist :)
- It will be really interesting to see how a ML algorithm solves this challenge.

3 Model Architecture

3.1 Create the training & validation sets

[330]:
```
train_df, valid_df = train_test_split(train_data, test_size=0.25,␣
↪random_state=42, stratify=train_data.label)

train_df.shape, valid_df.shape
```

[330]: ((165018, 2), (55007, 2))

[331]:
```
train_df['id'] = train_df['id'] + '.tif'
valid_df['id'] = valid_df['id'] + '.tif'
```

[332]:
```
# train_datagen below complains if the label values aren't string
train_df['label'] = train_df['label'].astype(str)
```

```
valid_df['label'] = valid_df['label'].astype(str)
```

[76]:
```
train_datagen=ImageDataGenerator(
    rescale=1/255
)

train_generator=train_datagen.
 ↪flow_from_dataframe(dataframe=train_df,directory=train_path,
                x_col="id",y_col="label",batch_size=32,seed=42,shuffle=True,
                class_mode="binary",target_size=(96,96))

valid_generator=train_datagen.
 ↪flow_from_dataframe(dataframe=valid_df,directory=train_path,
                x_col="id",y_col="label",batch_size=32,seed=42,shuffle=True,
                class_mode="binary",target_size=(96,96))
```

```
Found 165018 validated image filenames belonging to 2 classes.
Found 55007 validated image filenames belonging to 2 classes.
```

3.2 Define helper functions

[339]:
```
import itertools
def plot_confusion_matrix(cm, classes,title='Confusion matrix', cmap=plt.cm.
 ↪Blues):
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)
    fmt = 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[1]), range(cm.shape[0])):
        plt.text(j, i, format(cm[i, j], fmt),
        horizontalalignment="center",
        color="white" if cm[i, j] > thresh else "black")
    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')

def evaluate_model(history, model, X_validation, y_validation):
    if history is not None:
        plt.plot(history.history['accuracy'])
        plt.plot(history.history['val_accuracy'])
        plt.title('Model One Accuracy per Epoch')
        plt.ylabel('accuracy')
        plt.xlabel('epoch')
```

```
        plt.legend(['train', 'validate'], loc='upper left')
        plt.show();

        # plot model loss per epoch
        plt.plot(history.history['loss'])
        plt.plot(history.history['val_loss'])
        plt.title('Model One Loss per Epoch')
        plt.ylabel('loss')
        plt.xlabel('epoch')
        plt.legend(['train', 'validate'], loc='upper left')
        plt.show();

    # Show confusion matirx
    y_valid_pred = model.predict(X_validation)
    y_valid_pred = [0 if pred < 0.5 else 1 for pred in y_valid_pred]
    cm_train = np.flip(confusion_matrix(y_validation, y_valid_pred))
    plot_confusion_matrix(cm_train,["Non-cancerous tissue", "Cancerous tissue"])
    plt.show();

    # Calculate the fun metrics
    print(f'Total images with cancerous tissue detected in validation set:␣
↪{cm_train[1][1]} of {cm_train[1][1]+cm_train[1][0]}')
    print(f'Total images with no cancerous tissue detected in validation set:␣
↪{cm_train[0][0]} of {cm_train[0][1]+cm_train[0][0]}')
    print(f'Probability to detect a image with cancerous tissue  in the␣
↪validation set: {cm_train[1][1]/(cm_train[1][1]+cm_train[1][0]):0.2f}')
    print(f'Probability to detect a image with no cancerous tissue  tweet in␣
↪the validation set: {(cm_train[0][0]/(cm_train[0][1]+cm_train[0][0])):0.2f}')
    print(f"Accuracy of unsupervised model on the validation set:␣
↪{100*(accuracy_score(y_validation, y_valid_pred)):0.2f}%")
```

3.3 Create the baseline model

[210]:
```
model = Sequential()

model.add(Input(shape=(96,96,3)))
model.add(Conv2D(32, (3, 3), padding='same'))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Flatten())
model.add(Dense(32))
model.add(Activation('relu'))

model.add(Dense(1, activation='sigmoid'))
opt = tf.keras.optimizers.Adam(0.001)
```

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

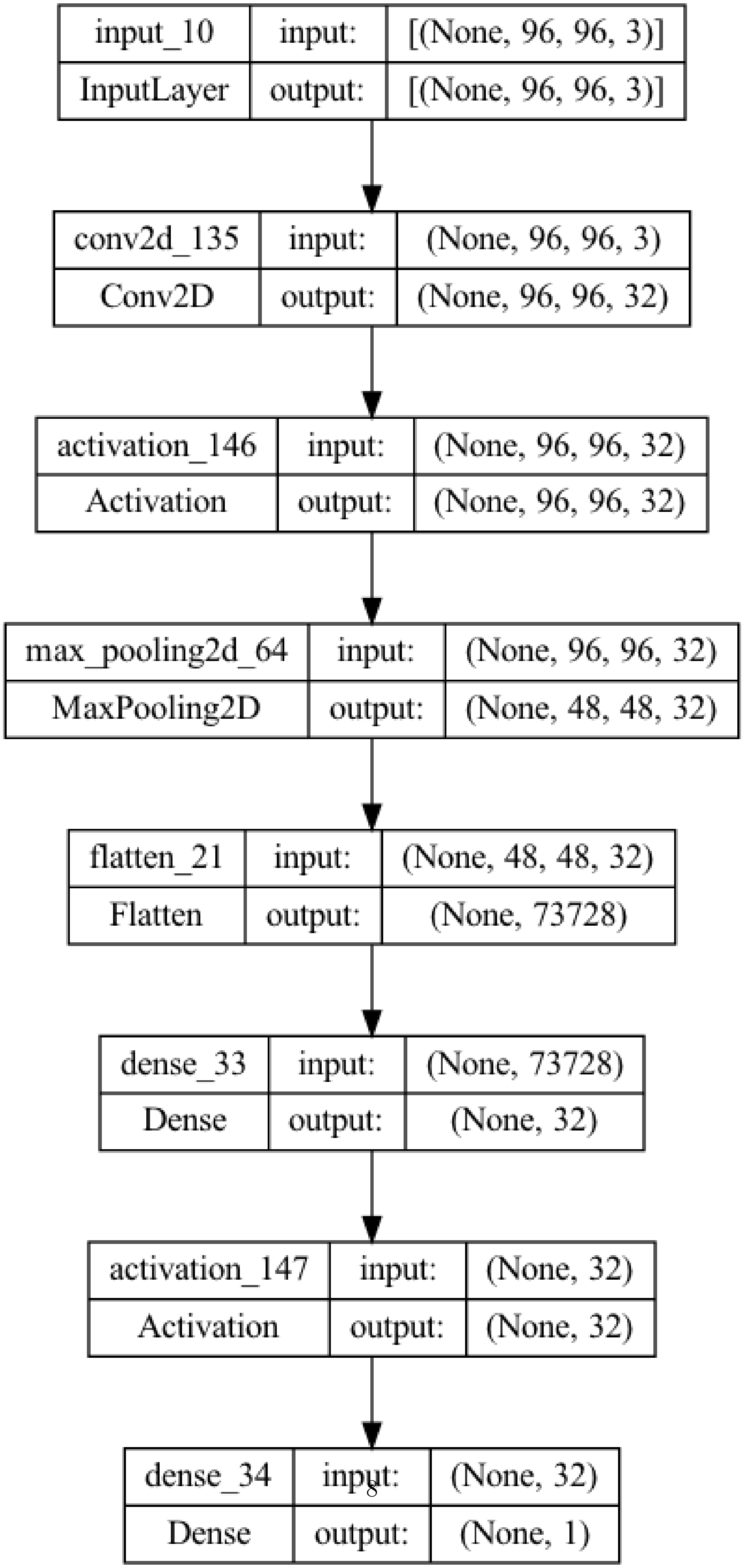
[211]:
```
model.summary()
```

```
Model: "sequential_27"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_135 (Conv2D)         (None, 96, 96, 32)        896

 activation_146 (Activation)  (None, 96, 96, 32)       0

 max_pooling2d_64 (MaxPoolin  (None, 48, 48, 32)       0
 g2D)

 flatten_21 (Flatten)        (None, 73728)             0

 dense_33 (Dense)            (None, 32)                2359328

 activation_147 (Activation)  (None, 32)               0

 dense_34 (Dense)            (None, 1)                 33

=================================================================
Total params: 2,360,257
Trainable params: 2,360,257
Non-trainable params: 0
_________________________________________________________________
```

Flowchart of the baseline model

[212]:
```
tf.keras.utils.plot_model(model, show_shapes=True)
```

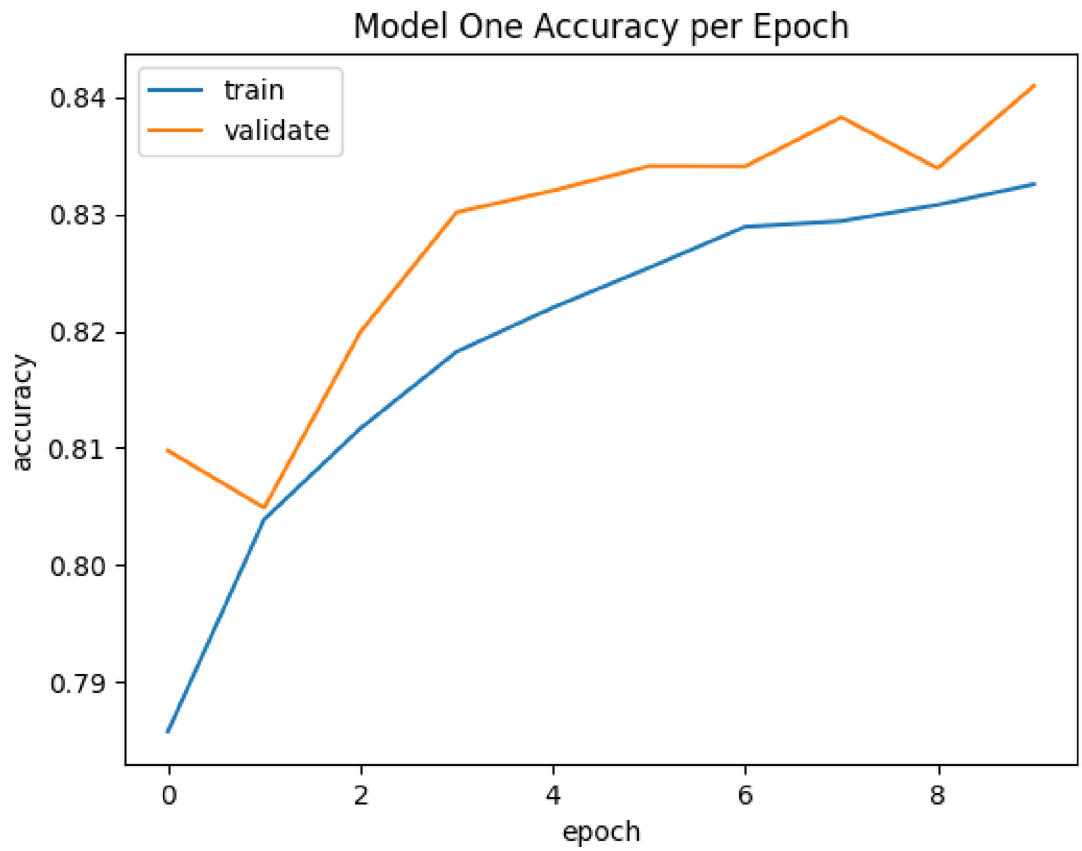
[212]:

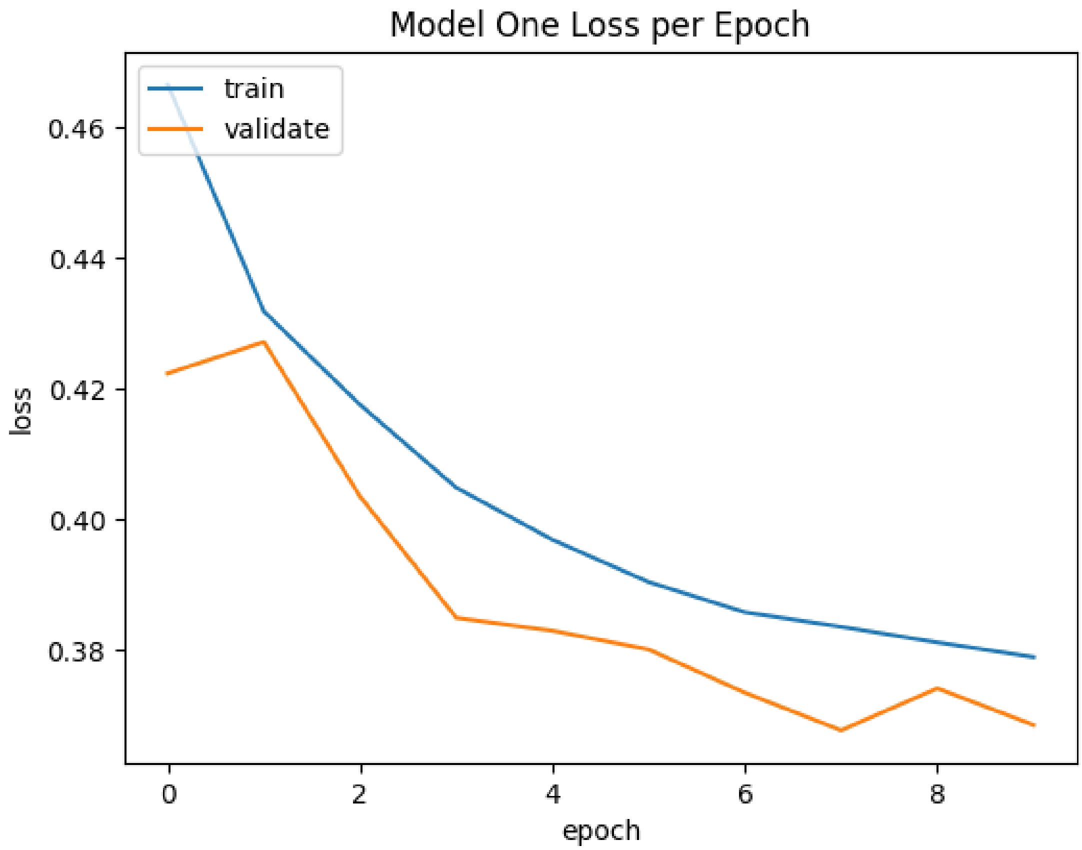

input_10
InputLayer
input:
output:
[(None, 96, 96, 3)]
[(None, 96, 96, 3)]
conv2d_135
Conv2D
input:
output:
(None, 96, 96, 3)
(None, 96, 96, 32)
activation_146
Activation
input:
output:
(None, 96, 96, 32)
(None, 96, 96, 32)
max_pooling2d_64
MaxPooling2D
input:
output:
(None, 96, 96, 32)
(None, 48, 48, 32)
flatten_21
Flatten
input:
output:
(None, 48, 48, 32)
(None, 73728)
dense_33
Dense
input:
output:
(None, 73728)
(None, 32)
activation_147
Activation
input:
output:
(None, 32)
(None, 32)
dense_34
Dense
input:
output:
(None, 32)
(None, 1)

[213]:
```
history = model.fit(train_generator,
                    validation_data=valid_generator,
                    epochs=10, verbose=1
)
```

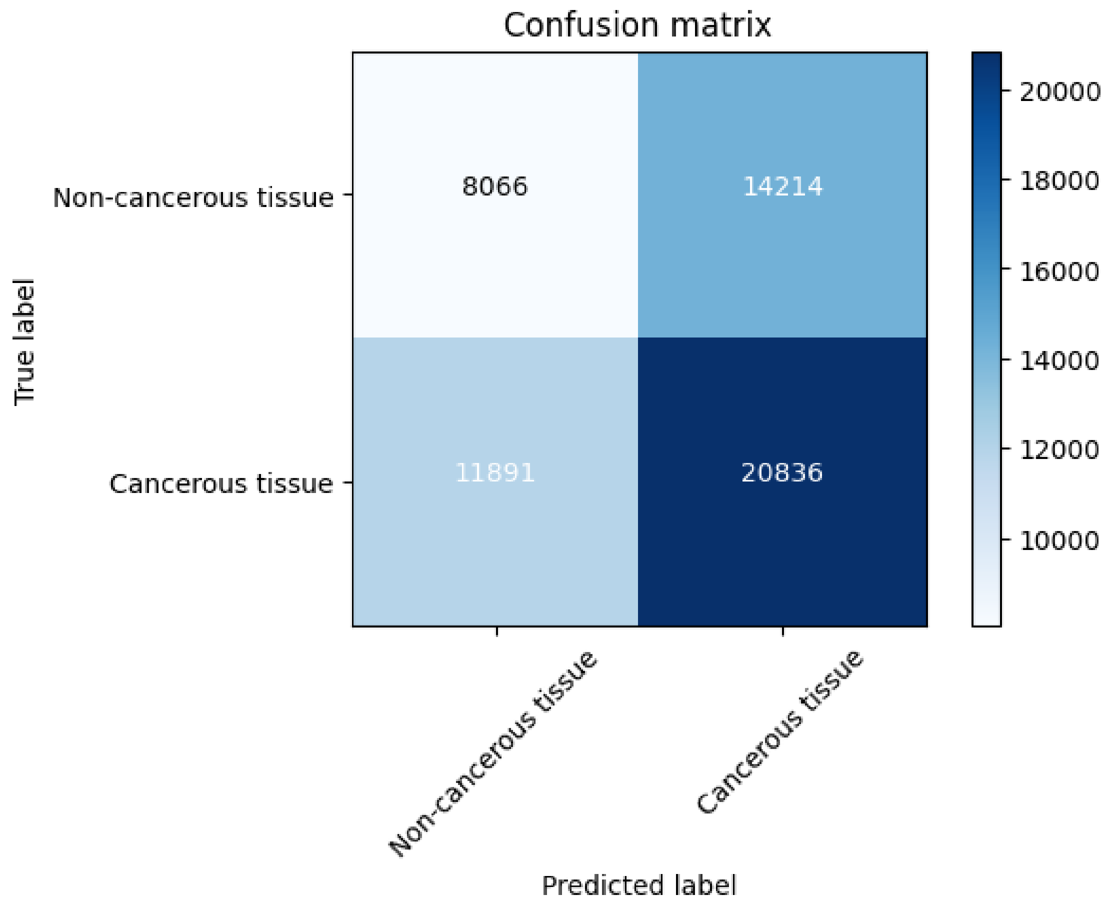
```
Epoch 1/10

2022-10-10 15:48:49.180690: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.

5157/5157 [==============================] - ETA: 0s - loss: 0.4666 - accuracy:
0.7858

2022-10-10 15:52:15.468257: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.

5157/5157 [==============================] - 271s 52ms/step - loss: 0.4666 -
accuracy: 0.7858 - val_loss: 0.4223 - val_accuracy: 0.8098
Epoch 2/10
5157/5157 [==============================] - 256s 50ms/step - loss: 0.4318 -
accuracy: 0.8039 - val_loss: 0.4271 - val_accuracy: 0.8049
Epoch 3/10
5157/5157 [==============================] - 258s 50ms/step - loss: 0.4175 -
accuracy: 0.8117 - val_loss: 0.4034 - val_accuracy: 0.8199
Epoch 4/10
5157/5157 [==============================] - 257s 50ms/step - loss: 0.4048 -
accuracy: 0.8182 - val_loss: 0.3848 - val_accuracy: 0.8301
Epoch 5/10
5157/5157 [==============================] - 258s 50ms/step - loss: 0.3968 -
accuracy: 0.8220 - val_loss: 0.3829 - val_accuracy: 0.8320
Epoch 6/10
5157/5157 [==============================] - 257s 50ms/step - loss: 0.3903 -
accuracy: 0.8254 - val_loss: 0.3800 - val_accuracy: 0.8341
Epoch 7/10
5157/5157 [==============================] - 260s 50ms/step - loss: 0.3857 -
accuracy: 0.8289 - val_loss: 0.3734 - val_accuracy: 0.8341
Epoch 8/10
5157/5157 [==============================] - 258s 50ms/step - loss: 0.3835 -
accuracy: 0.8294 - val_loss: 0.3676 - val_accuracy: 0.8383
Epoch 9/10
5157/5157 [==============================] - 257s 50ms/step - loss: 0.3811 -
accuracy: 0.8308 - val_loss: 0.3740 - val_accuracy: 0.8339
Epoch 10/10
5157/5157 [==============================] - 257s 50ms/step - loss: 0.3788 -
accuracy: 0.8325 - val_loss: 0.3684 - val_accuracy: 0.8409
```

[228]:
```
evaluate_model(history, model, valid_generator, valid_generator.labels)
```






```
1719/1719 [==============================] - 65s 38ms/step
```




```
Total images with cancerous tissue detected in validation set: 20836 of 32727
Total images with no cancerous tissue detected in validation set: 8066 of 22280
Probability to detect a image with cancerous tissue  in the validation set: 0.64
Probability to detect a image with no cancerous tissue  tweet in the validation
set: 0.36
Accuracy of unsupervised model on the validation set: 52.54%
```

- Validation accuracy pleateous after approx. 7 epochs while training accuracy keeps going up
  1. The model's most likely over-fitting.
  2. The model has *learnt* as many intricricacies from the training data as it could but hasn't been able to generalize it enough to perform better on the validation set.
- Potential fixes:
  - Add image augmentation layers such as `RandomFlip` and `RandomRotation` to help the model gain more information from our training data. These layers help create *new* data from the existing dataset by flipping or rotating the images. Therefore, helping the model become more generalizable.
  - Add `Dropout` layers
  - Reduce the learning rate
  - Reduce the # of layers

    – Reduce the # of epochs

- Let's first try adding the image augmentation layers & dropout layers mentioned above. If the scores don't improve, we can implement the other fixes as well.

3.4 Train a bigger, better model

[334]:
```
train_datagen = ImageDataGenerator(
    rescale=1/255,
    rotation_range=10,
    horizontal_flip=True,
    vertical_flip=True
)

train_generator = train_datagen.
 ↪flow_from_dataframe(dataframe=train_df,directory=train_path,
                                                         ␣
 ↪x_col="id",y_col="label",batch_size=32,seed=42,shuffle=True,
                                                         ␣
 ↪class_mode="binary",target_size=(96,96))

valid_generator = train_datagen.
 ↪flow_from_dataframe(dataframe=valid_df,directory=train_path,
                                                         ␣
 ↪x_col="id",y_col="label",batch_size=32,seed=42,shuffle=True,
                                                         ␣
 ↪class_mode="binary",target_size=(96,96))
```

```
Found 165018 validated image filenames belonging to 2 classes.
Found 55007 validated image filenames belonging to 2 classes.
```

- Due to a bug in Tensorflow 2.9 & above (I'm using 2.10), I can't use any of the image preprocessing layers directly in the model definition. Adding these layers caused my model training to slow down by 5-6x.
- Therefore, I've added these preprocessing steps into the `ImageDataGenerator` object directly. I've set the `seed` to the exact same value as the `ImageDataGenerator` for previous model's data to ensure the same samples go into the training & validation dataset.

[335]:
```
model2 = Sequential()

model2.add(Input(shape=(96,96,3)))

model2.add(Conv2D(32, (3, 3), padding='same'))
model2.add(Activation('relu'))
model2.add(BatchNormalization())
model2.add(MaxPooling2D(pool_size=(2, 2)))


model2.add(Conv2D(64, (3, 3), padding="same"))
```

```
model2.add(Activation('relu'))
model2.add(BatchNormalization())
model2.add(Conv2D(64, (3, 3), padding="same"))
model2.add(Activation('relu'))
model2.add(BatchNormalization())
model2.add(AveragePooling2D(pool_size=(2, 2)))
model2.add(Dropout(0.25))

model2.add(Conv2D(128, (3, 3), padding='same'))
model2.add(Activation('relu'))
model2.add(BatchNormalization())
model2.add(Conv2D(128, (3, 3), padding='same'))
model2.add(Activation('relu'))
model2.add(BatchNormalization())
model2.add(Conv2D(128, (3, 3), padding='same'))
model2.add(Activation('relu'))
model2.add(BatchNormalization())
model2.add(AveragePooling2D(pool_size=(2, 2)))

model2.add(Flatten())
model2.add(Dropout(0.5))
model2.add(Dense(64))
model2.add(Activation('relu'))
model2.add(BatchNormalization())
model2.add(Dense(1, activation='sigmoid'))

opt = tf.keras.optimizers.Adam(1e-4)
metric_AUC = tf.keras.metrics.AUC()
model2.compile(loss='binary_crossentropy', optimizer=opt, metrics=['accuracy',␣
 ↪metric_AUC])
```

- Adding AUC as a metric to improve the analysis of this model
- ROC curves are a quality measures of binary classifiers. They evaluate all the operational points of a model.
- The metric calculates 4 new measures : `true_positives`, `true_negatives`, `false_positives` and `false_negatives`. These measures can then be used to calculate F1-scores, precision and recall. These metrics allow us to further test the validity of the model.

[336]:
```
model2.summary()
```

```
Model: "sequential_42"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_178 (Conv2D)         (None, 96, 96, 32)        896


 activation_204 (Activation)  (None, 96, 96, 32)       0
```

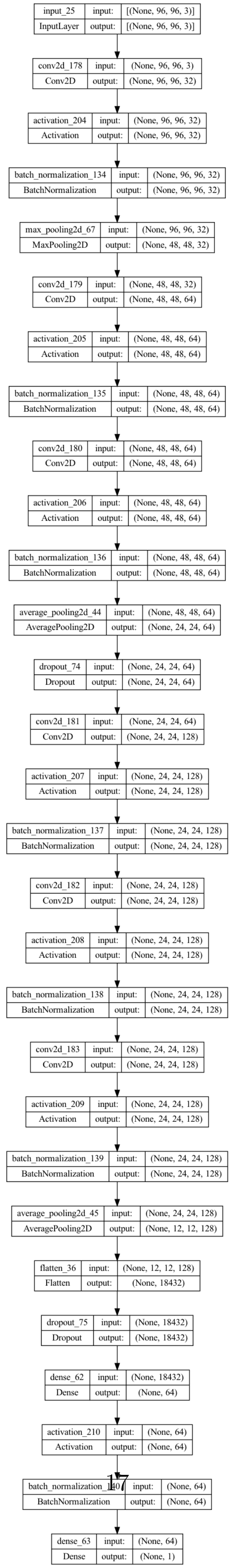
```
batch_normalization_134 (Ba  (None, 96, 96, 32)       128
tchNormalization)

max_pooling2d_67 (MaxPoolin  (None, 48, 48, 32)       0
g2D)

conv2d_179 (Conv2D)         (None, 48, 48, 64)        18496

activation_205 (Activation)  (None, 48, 48, 64)       0

batch_normalization_135 (Ba  (None, 48, 48, 64)       256
tchNormalization)

conv2d_180 (Conv2D)         (None, 48, 48, 64)        36928

activation_206 (Activation)  (None, 48, 48, 64)       0

batch_normalization_136 (Ba  (None, 48, 48, 64)       256
tchNormalization)

average_pooling2d_44 (Avera  (None, 24, 24, 64)       0
gePooling2D)

dropout_74 (Dropout)        (None, 24, 24, 64)        0

conv2d_181 (Conv2D)         (None, 24, 24, 128)       73856

activation_207 (Activation)  (None, 24, 24, 128)      0

batch_normalization_137 (Ba  (None, 24, 24, 128)      512
tchNormalization)

conv2d_182 (Conv2D)         (None, 24, 24, 128)       147584

activation_208 (Activation)  (None, 24, 24, 128)      0

batch_normalization_138 (Ba  (None, 24, 24, 128)      512
tchNormalization)

conv2d_183 (Conv2D)         (None, 24, 24, 128)       147584

activation_209 (Activation)  (None, 24, 24, 128)      0

batch_normalization_139 (Ba  (None, 24, 24, 128)      512
tchNormalization)

average_pooling2d_45 (Avera  (None, 12, 12, 128)      0
```

```
 gePooling2D)

 flatten_36 (Flatten)        (None, 18432)             0

 dropout_75 (Dropout)        (None, 18432)             0

 dense_62 (Dense)            (None, 64)                1179712

 activation_210 (Activation)  (None, 64)               0

 batch_normalization_140 (Ba  (None, 64)               256
 tchNormalization)

 dense_63 (Dense)            (None, 1)                 65

=================================================================
Total params: 1,607,553
Trainable params: 1,606,337
Non-trainable params: 1,216
_________________________________________________________________
```

Flowchart of the bigger model

[337]:
```
tf.keras.utils.plot_model(model2, show_shapes=True)
```

[337]:


input_25 | input: | [(None, 96, 96, 3)]
InputLayer | output: | [(None, 96, 96, 3)]
conv2d_178 | input: | (None, 96, 96, 3)
Conv2D | output: | (None, 96, 96, 32)
activation_204 | input: | (None, 96, 96, 32)
Activation | output: | (None, 96, 96, 32)
batch_normalization_134 | input: | (None, 96, 96, 32)
BatchNormalization | output: | (None, 96, 96, 32)
max_pooling2d_67 | input: | (None, 96, 96, 32)
MaxPooling2D | output: | (None, 48, 48, 32)
conv2d_179 | input: | (None, 48, 48, 32)
Conv2D | output: | (None, 48, 48, 64)
activation_205 | input: | (None, 48, 48, 64)
Activation | output: | (None, 48, 48, 64)
batch_normalization_135 | input: | (None, 48, 48, 64)
BatchNormalization | output: | (None, 48, 48, 64)
conv2d_180 | input: | (None, 48, 48, 64)
Conv2D | output: | (None, 48, 48, 64)
activation_206 | input: | (None, 48, 48, 64)
Activation | output: | (None, 48, 48, 64)
batch_normalization_136 | input: | (None, 48, 48, 64)
BatchNormalization | output: | (None, 48, 48, 64)
average_pooling2d_44 | input: | (None, 48, 48, 64)
AveragePooling2D | output: | (None, 24, 24, 64)
dropout_74 | input: | (None, 24, 24, 64)
Dropout | output: | (None, 24, 24, 64)
conv2d_181 | input: | (None, 24, 24, 64)
Conv2D | output: | (None, 24, 24, 128)
activation_207 | input: | (None, 24, 24, 128)
Activation | output: | (None, 24, 24, 128)
batch_normalization_137 | input: | (None, 24, 24, 128)
BatchNormalization | output: | (None, 24, 24, 128)
conv2d_182 | input: | (None, 24, 24, 128)
Conv2D | output: | (None, 24, 24, 128)
activation_208 | input: | (None, 24, 24, 128)
Activation | output: | (None, 24, 24, 128)
batch_normalization_138 | input: | (None, 24, 24, 128)
BatchNormalization | output: | (None, 24, 24, 128)
conv2d_183 | input: | (None, 24, 24, 128)
Conv2D | output: | (None, 24, 24, 128)
activation_209 | input: | (None, 24, 24, 128)
Activation | output: | (None, 24, 24, 128)
batch_normalization_139 | input: | (None, 24, 24, 128)
BatchNormalization | output: | (None, 24, 24, 128)
average_pooling2d_45 | input: | (None, 24, 24, 128)
AveragePooling2D | output: | (None, 12, 12, 128)
flatten_36 | input: | (None, 12, 12, 128)
Flatten | output: | (None, 18432)
dropout_75 | input: | (None, 18432)
Dropout | output: | (None, 18432)
dense_62 | input: | (None, 18432)
Dense | output: | (None, 64)
activation_210 | input: | (None, 64)
Activation | output: | (None, 64)
batch_normalization_140 | input: | (None, 64)
BatchNormalization | output: | (None, 64)
dense_63 | input: | (None, 64)
Dense | output: | (None, 1)

[237]:
```
early_stop = EarlyStopping(monitor='val_accuracy', patience=2)
reduce_lr = ReduceLROnPlateau(monitor='val_accuracy', factor=0.2, patience=2,
                              verbose=1, mode='max', min_lr=0.00001)
model_dir = './best_model/model2_best.h5'
checkpoint = ModelCheckpoint(model_dir, monitor='val_accuracy', verbose=1,
                             save_best_only=True, mode='max')


callbacks_list = [early_stop, reduce_lr, checkpoint]
```

- I have added a `checkpoint` callback to the list to save the best model since the model generated at the last epoch isn't necessarily the best one.
- The evidence of this can be found in the accuracy plot for previous model, the last model had a significantly fewer accuracy than the one at epoch #3.

[238]:
```
history2 = model2.fit(train_generator,
                      validation_data=valid_generator,
                      epochs=10, verbose=1, callbacks=callbacks_list
)
```

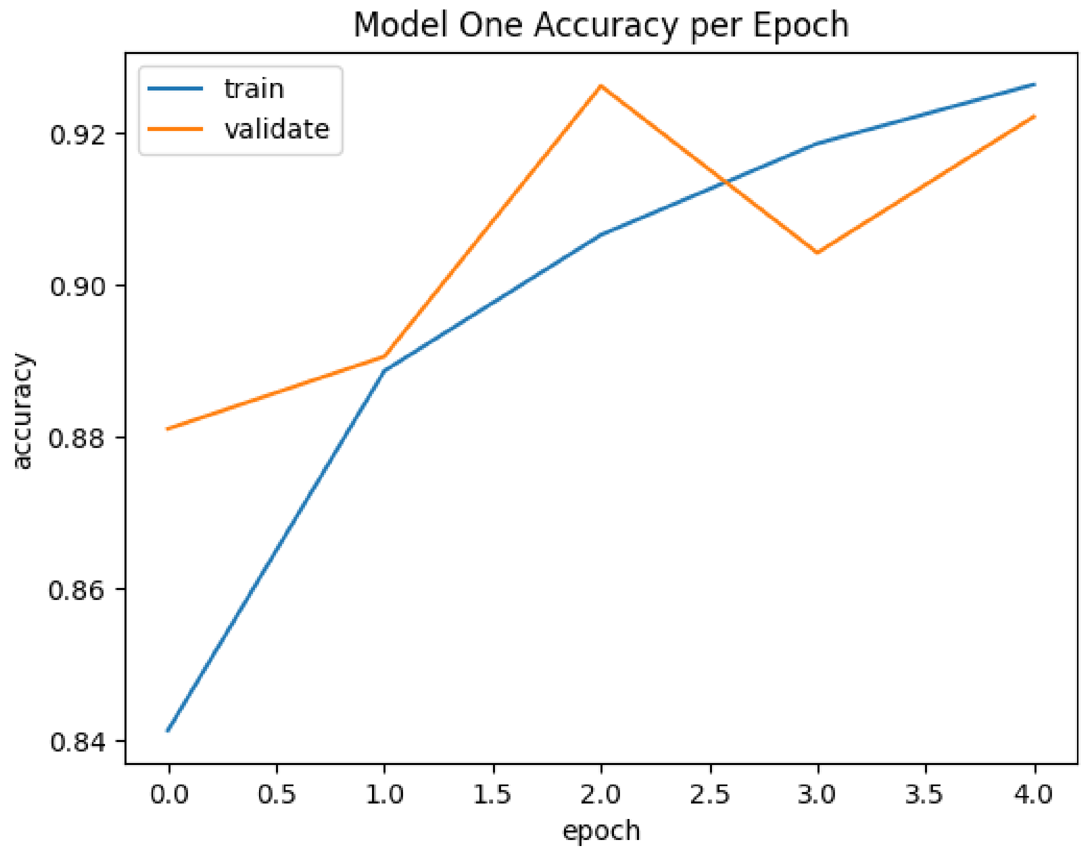
```
Epoch 1/10

2022-10-10 16:55:07.903755: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.

5156/5157 [============================>.] - ETA: 0s - loss: 0.3683 - accuracy:
0.8413 - auc_7: 0.9116

2022-10-10 16:58:45.324350: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.


Epoch 1: val_accuracy improved from -inf to 0.88102, saving model to
./best_model/model2_best.h5
5157/5157 [==============================] - 282s 54ms/step - loss: 0.3683 -
accuracy: 0.8413 - auc_7: 0.9116 - val_loss: 0.2817 - val_accuracy: 0.8810 -
val_auc_7: 0.9502 - lr: 1.0000e-04
Epoch 2/10
5157/5157 [==============================] - ETA: 0s - loss: 0.2734 - accuracy:
0.8886 - auc_7: 0.9515
Epoch 2: val_accuracy improved from 0.88102 to 0.89054, saving model to
./best_model/model2_best.h5
5157/5157 [==============================] - 284s 55ms/step - loss: 0.2734 -
accuracy: 0.8886 - auc_7: 0.9515 - val_loss: 0.2750 - val_accuracy: 0.8905 -
val_auc_7: 0.9516 - lr: 1.0000e-04
```

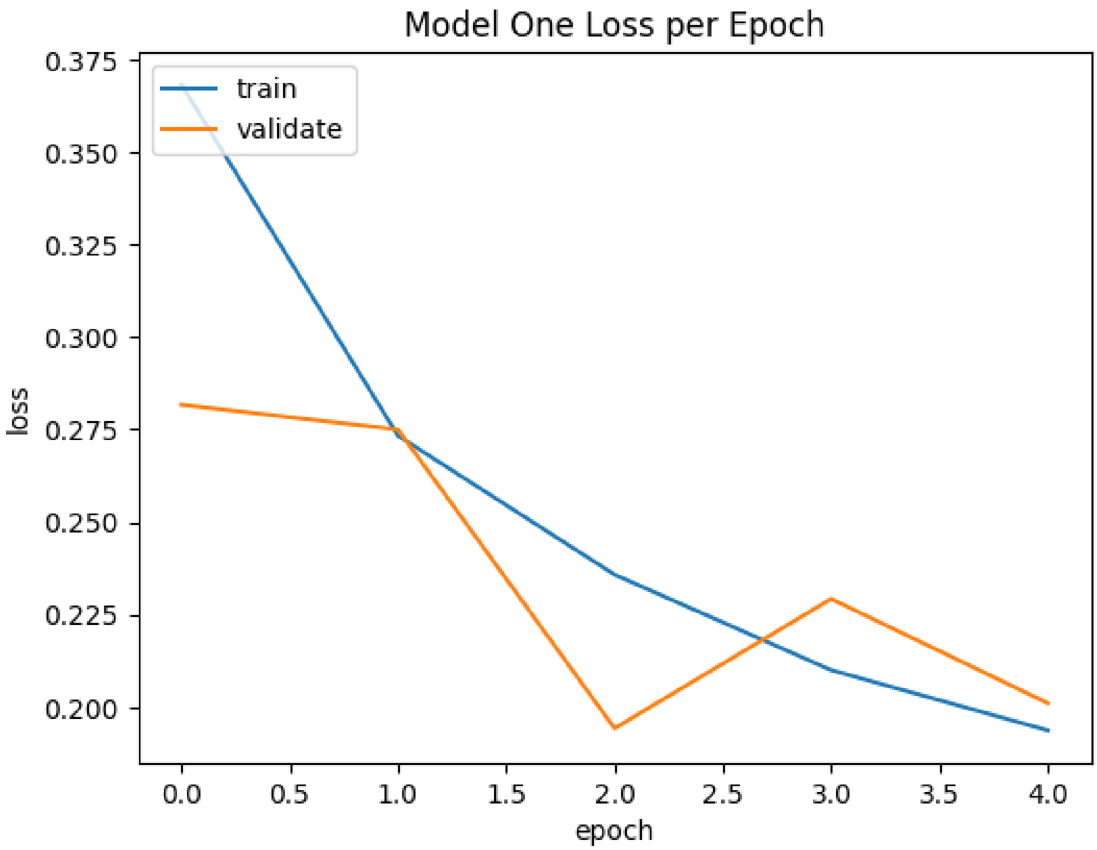
```
Epoch 3/10
5156/5157 [============================>.] - ETA: 0s - loss: 0.2358 - accuracy:
0.9065 - auc_7: 0.9635
Epoch 3: val_accuracy improved from 0.89054 to 0.92619, saving model to
./best_model/model2_best.h5
5157/5157 [==============================] - 281s 54ms/step - loss: 0.2358 -
accuracy: 0.9066 - auc_7: 0.9635 - val_loss: 0.1942 - val_accuracy: 0.9262 -
val_auc_7: 0.9764 - lr: 1.0000e-04
Epoch 4/10
5156/5157 [============================>.] - ETA: 0s - loss: 0.2100 - accuracy:
0.9186 - auc_7: 0.9706
Epoch 4: val_accuracy did not improve from 0.92619
5157/5157 [==============================] - 281s 55ms/step - loss: 0.2100 -
accuracy: 0.9186 - auc_7: 0.9706 - val_loss: 0.2292 - val_accuracy: 0.9042 -
val_auc_7: 0.9687 - lr: 1.0000e-04
Epoch 5/10
5156/5157 [============================>.] - ETA: 0s - loss: 0.1937 - accuracy:
0.9264 - auc_7: 0.9747
Epoch 5: ReduceLROnPlateau reducing learning rate to 1.9999999494757503e-05.

Epoch 5: val_accuracy did not improve from 0.92619
5157/5157 [==============================] - 279s 54ms/step - loss: 0.1937 -
accuracy: 0.9264 - auc_7: 0.9747 - val_loss: 0.2011 - val_accuracy: 0.9221 -
val_auc_7: 0.9740 - lr: 1.0000e-04
```

Load the best model

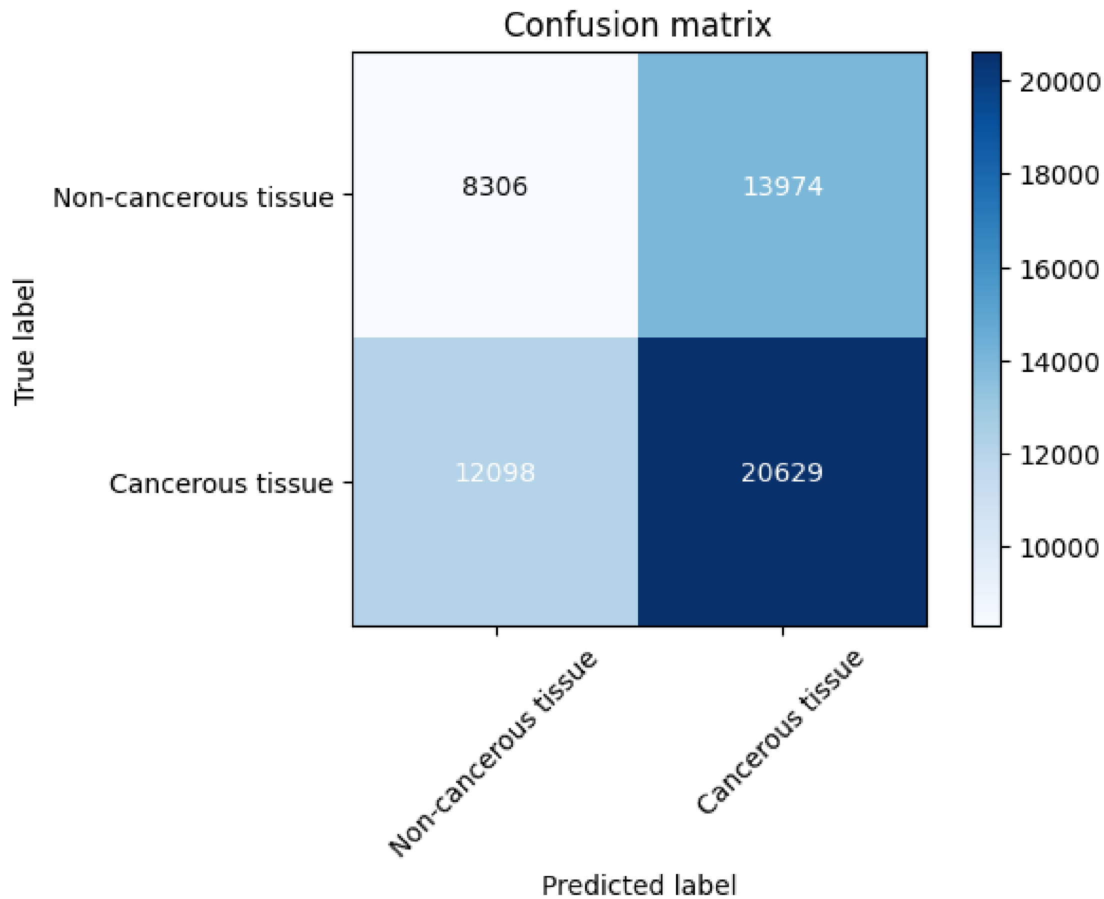
[242]:
```python
from tensorflow.keras.models import load_model
model2_best = load_model('./best_model/model2_best.h5')
```

[243]:
```python
evaluate_model(history2, model2_best, valid_generator, valid_generator.labels)
```


Model One Accuracy per Epoch
train
validate
0.92
0.90
0.88
0.86
0.84
accuracy
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
epoch




```
   1/1719 […] - ETA: 6:12
2022-10-10 17:24:43.168164: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.
1719/1719 [==============================] - 65s 38ms/step
```




```
Total images with cancerous tissue detected in validation set: 20629 of 32727
Total images with no cancerous tissue detected in validation set: 8306 of 22280
Probability to detect a image with cancerous tissue  in the validation set: 0.63
Probability to detect a image with no cancerous tissue  tweet in the validation
set: 0.37
Accuracy of unsupervised model on the validation set: 52.60%
```

- The *bigger and better* model only improved marginally over the baseline model :(
- Ability to detect an image with cancerous tissue actually went down by 0.1%
- However, the overall accuracy went up by 0.1%

3.5 Hyperparameter Tuning

[245]:
```
from keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import GridSearchCV
```

[248]:
```
def build_model(num_conv_layers=1, dropout_level=0.5, learning_rate=1e-3):

    nn = Sequential()
```

```
    nn.add(Input(shape=(96,96,3)))


    for i in range(num_conv_layers):
        nn.add(Conv2D(64, (3, 3), padding="same"))
        nn.add(Activation('relu'))
        nn.add(BatchNormalization())
        nn.add(AveragePooling2D(pool_size=(2, 2)))
        nn.add(Dropout(dropout_level))

    nn.add(Flatten())
    nn.add(Dense(64))
    nn.add(Activation('relu'))
    nn.add(BatchNormalization())
    nn.add(Dense(1, activation='sigmoid'))

    opt = tf.keras.optimizers.Adam(learning_rate)
    nn.compile(loss='binary_crossentropy',optimizer=opt,metrics=['accuracy'])

    return nn
```

[341]:
```
parameters = {
    'epochs': [5, 10],
    'num_conv_layers': [1, 2, 4, 6]
}
```

[342]:
```
total_combs = len(parameters['epochs']) * len(parameters['num_conv_layers'])
```

- Writing a custom grid search utility here since `GridSearchCV` doesn't work with `ImageGenerator` datasets.
- I searched around for a solution to this problem but to no avail.

[344]:
```
early_stop = EarlyStopping(monitor='val_accuracy', patience=2)
reduce_lr = ReduceLROnPlateau(monitor='val_accuracy', factor=0.2, patience=2,
                                   verbose=1, mode='max', min_lr=0.00001)
model_dir = './best_model/model_gridsearch_best.h5'
checkpoint = ModelCheckpoint(model_dir, monitor='val_accuracy', verbose=1,
                             save_best_only=True, mode='max')

callbacks_list = [early_stop, reduce_lr, checkpoint]

i=0
print(f'Evaluating a total of {total_combs} combinations\n')

for epoch in parameters['epochs']:
    for num_layers in parameters['num_conv_layers']:
```

```
        print(f'Evaluating combination {i+1} of {total_combs} with epoch =␣
↪{epoch} and number of conv layers = {num_layers}')
        model = build_model(num_layers)
        history = model.fit(train_generator,
                    validation_data=valid_generator,
                    epochs=epoch, verbose=0, callbacks=callbacks_list)
        i+=1
       ␣
↪print('===========================================================================')
```

```
Evaluating a total of 8 combinations

Evaluating combination 1 of 8 with epoch = 5 and number of conv layers = 1

2022-10-10 22:27:24.195762: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.
2022-10-10 22:34:56.160832: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.


Epoch 1: val_accuracy improved from -inf to 0.80484, saving model to
./best_model/model_gridsearch_best.h5

Epoch 2: val_accuracy did not improve from 0.80484

Epoch 3: val_accuracy improved from 0.80484 to 0.81782, saving model to
./best_model/model_gridsearch_best.h5

Epoch 4: val_accuracy did not improve from 0.81782

Epoch 5: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.

Epoch 5: val_accuracy did not improve from 0.81782
===========================================================================
Evaluating combination 2 of 8 with epoch = 5 and number of conv layers = 2

2022-10-10 23:13:02.206425: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.
2022-10-10 23:16:52.045121: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.


Epoch 1: val_accuracy improved from 0.81782 to 0.83046, saving model to
./best_model/model_gridsearch_best.h5
```

```
Epoch 2: val_accuracy did not improve from 0.83046

Epoch 3: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.

Epoch 3: val_accuracy did not improve from 0.83046
===========================================================================
Evaluating combination 3 of 8 with epoch = 5 and number of conv layers = 4

2022-10-10 23:27:44.390132: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.
2022-10-10 23:31:31.759467: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.


Epoch 1: val_accuracy improved from 0.83046 to 0.86487, saving model to
./best_model/model_gridsearch_best.h5

Epoch 2: val_accuracy did not improve from 0.86487

Epoch 3: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.

Epoch 3: val_accuracy did not improve from 0.86487
===========================================================================
Evaluating combination 4 of 8 with epoch = 5 and number of conv layers = 6

2022-10-10 23:42:09.529042: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.
2022-10-10 23:46:05.119681: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.


Epoch 1: val_accuracy did not improve from 0.86487

Epoch 2: val_accuracy did not improve from 0.86487

Epoch 3: val_accuracy did not improve from 0.86487

Epoch 4: val_accuracy did not improve from 0.86487

Epoch 5: val_accuracy did not improve from 0.86487
===========================================================================
Evaluating combination 5 of 8 with epoch = 10 and number of conv layers = 1

2022-10-11 00:06:58.216810: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.
```

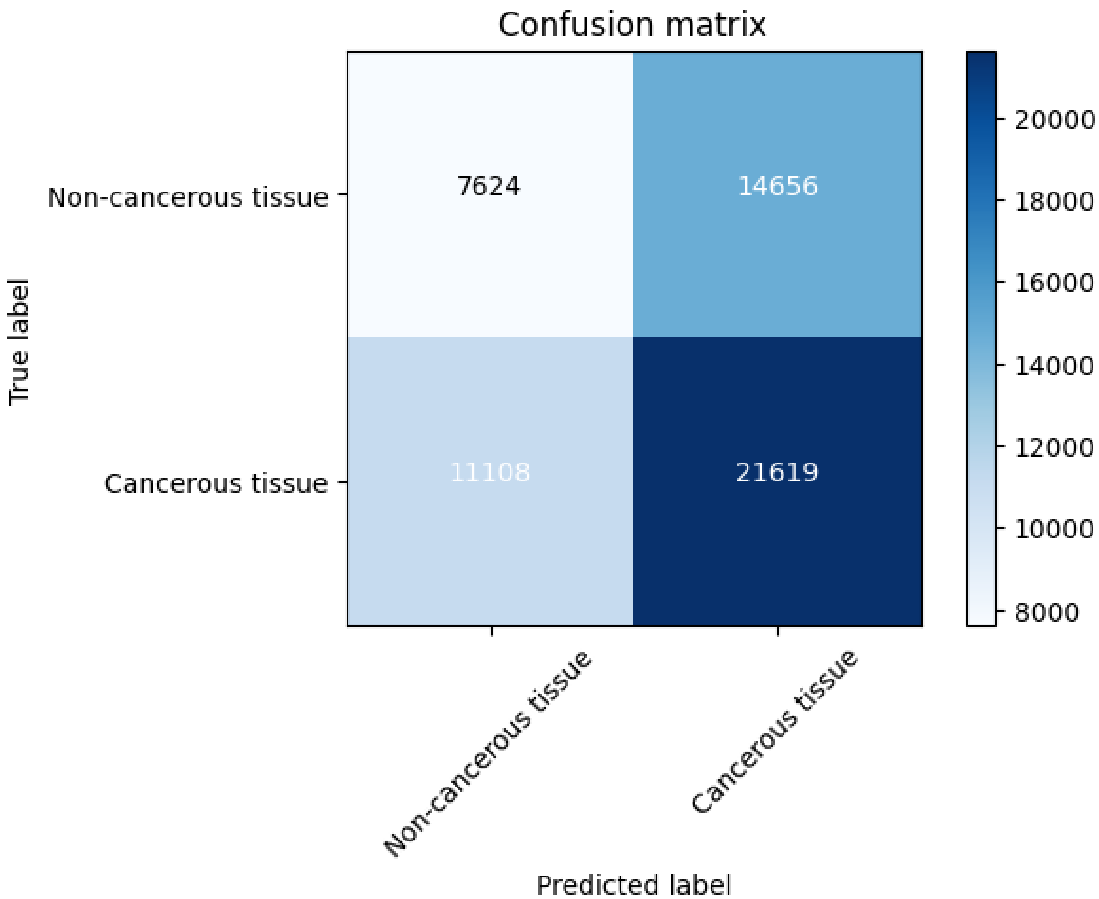
```
2022-10-11 00:14:26.084801: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.


Epoch 1: val_accuracy did not improve from 0.86487

Epoch 2: val_accuracy did not improve from 0.86487

Epoch 3: val_accuracy did not improve from 0.86487

Epoch 4: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.

Epoch 4: val_accuracy did not improve from 0.86487
===========================================================================
Evaluating combination 6 of 8 with epoch = 10 and number of conv layers = 2

2022-10-11 00:43:23.280417: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.
2022-10-11 00:47:13.359055: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.


Epoch 1: val_accuracy did not improve from 0.86487

Epoch 2: val_accuracy did not improve from 0.86487

Epoch 3: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.

Epoch 3: val_accuracy did not improve from 0.86487
===========================================================================
Evaluating combination 7 of 8 with epoch = 10 and number of conv layers = 4

2022-10-11 00:57:58.701650: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.
2022-10-11 01:01:46.517880: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.


Epoch 1: val_accuracy did not improve from 0.86487

Epoch 2: val_accuracy improved from 0.86487 to 0.87727, saving model to
./best_model/model_gridsearch_best.h5

Epoch 3: val_accuracy did not improve from 0.87727
```

```
Epoch 4: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.

Epoch 4: val_accuracy did not improve from 0.87727
===========================================================================
Evaluating combination 8 of 8 with epoch = 10 and number of conv layers = 6

2022-10-11 01:17:11.892039: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.
2022-10-11 01:21:07.118687: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.


Epoch 1: val_accuracy did not improve from 0.87727

Epoch 2: val_accuracy did not improve from 0.87727

Epoch 3: val_accuracy did not improve from 0.87727

Epoch 4: val_accuracy did not improve from 0.87727

Epoch 5: val_accuracy did not improve from 0.87727

Epoch 6: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.

Epoch 6: val_accuracy did not improve from 0.87727
===========================================================================
```

4 Results

[345]:
```
model_grid_best = load_model('./best_model/model_gridsearch_best.h5')
evaluate_model(None, model_grid_best, valid_generator, valid_generator.labels)
```

```
2022-10-11 07:11:10.494368: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.

1719/1719 [==============================] - 66s 38ms/step
```




```
Total images with cancerous tissue detected in validation set: 21619 of 32727
Total images with no cancerous tissue detected in validation set: 7624 of 22280
Probability to detect a image with cancerous tissue  in the validation set: 0.66
Probability to detect a image with no cancerous tissue  tweet in the validation
set: 0.34
Accuracy of unsupervised model on the validation set: 53.16%
```

- Hyperparameter tuning improved scores in certain areas while maintained the status quo in others when compared the second model.
- Drops
  - Probability of detecting a non-cancerous image went down by 1%
- Improvements
  - Overall accuracy went up by 1%
  - Probability of detecting a cancerous image went up by 2%
- Potential reasons behind the lackluster performance of a *hypertuned* model
  - The parameter grid is too small
  - Need more data to push into the model

5 Conclusion

- Early detection of cancer is a crucial problem to solve in the medical field. ML models can be a huge asset in solving this problem because they can churn through a vast amount of records faster than humans and flag cases down for doctors to analyse.
- My options of choosing which hyperparameters to tune were limited by GPU & time constraints.
  - Each epoch takes approximately 5 minutes to train.
  - The total # of epochs for the current parameter grid sits at 45 epochs. The current hyperparameter tuning took almost 45 epochs * 5 mins/epoch = 225 mins ~ 3.75 hours
- However, if I were to expand the parameters list, I would add the following
  - `learning_rate` for the optimizer
  - bigger range for number of `convolution` layers
  - bigger range for number of `epochs`
- Despite the long training time, the results proved *not worth* it. As mentioned above, there could be a multitude of reasons behind this. Some are easy to fix, i.e. expand the parameter grid whereas others are harder to accomplish, i.e. gather more data.
- For next steps, I would like to
  - Assemble a bigger training rig (with more GPUs, faster CPU and more RAM) to input significantly more data into the model. This will massively improve the generalization of the model.
  - Try huge pre-trained models such as Microsoft's ResNet or Google's VIT and train them to detect cancerous tissue in pathology scans.

6 Submission

[348]:
```
sample_submission = pd.read_csv('./histopathologic-cancer-detection/
 ↪sample_submission.csv')
sample_submission['id'] = sample_submission['id'] + '.tif'
sample_submission.head()
```

[348]:
```
                                             id  label
0  0b2ea2a822ad23fdb1b5dd26653da899fbd2c0d5.tif      0
1  95596b92e5066c5c52466c90b69ff089b39f2737.tif      0
2  248e6738860e2ebcf6258cdc1f32f299e0c76914.tif      0
3  2c35657e312966e9294eac6841726ff3a748febf.tif      0
4  145782eb7caa1c516acbe2eda34d9a3f31c41fd6.tif      0
```

[349]:
```
test_datagen = ImageDataGenerator(
    rescale=1/255
)
```

[350]:
```
test_generator=test_datagen.
 ↪flow_from_dataframe(dataframe=sample_submission,directory=test_path,
                                                  x_col="id",y_col=None,
                                                  batch_size=1,
                                                  class_mode=None,
```

```
                                target_size=(96,96))
```

```
Found 57458 validated image filenames.
```

[351]:
```
preds = model_grid_best.predict(test_generator)
```

```
2022-10-11 07:18:23.675076: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.
```

```
57458/57458 [==============================] - 127s 2ms/step
```

[352]:
```
preds[:10]
```

[352]:
```
array([[0.0315817 ],
       [0.9883537 ],
       [0.06659343],
       [0.7134974 ],
       [0.02017562],
       [0.02555803],
       [0.89811933],
       [0.9148148 ],
       [0.00711332],
       [0.07086378]], dtype=float32)
```

[353]:
```
np.unique(np.round(preds), return_counts=True)
```

[353]:
```
(array([0., 1.], dtype=float32), array([41992, 15466]))
```

[354]:
```
sample_submission['id'] = sample_submission['id'].apply(lambda x: x.split('.
 ↪')[0])
sample_submission['label'] = [0 if pred < 0.5 else 1 for pred in preds]
```

[355]:
```
sample_submission.head()
```

[355]:

	id	label
0	0b2ea2a822ad23fdb1b5dd26653da899fbd2c0d5	0
1	95596b92e5066c5c52466c90b69ff089b39f2737	1
2	248e6738860e2ebcf6258cdc1f32f299e0c76914	0
3	2c35657e312966e9294eac6841726ff3a748febf	1
4	145782eb7caa1c516acbe2eda34d9a3f31c41fd6	0

[356]:
```
sample_submission.to_csv("submission.csv", index=False)
```

[357]:
```
!kaggle competitions submit -c histopathologic-cancer-detection -f submission.
 ↪csv -m "hypertuned model"
```

```
100%|                    | 2.36M/2.36M [00:03<00:00, 715kB/s]
Successfully submitted to Histopathologic Cancer Detection
```