Project Scope and Description

What is the problem?

For this project we are tasked with implementing a convolutional neural network for a binary image classification problem. The images at hand are small image patches taken from larger digital pathology scans. The goal is to detect and identify metastatic cancer. A difficulty we will face when implementing the algorithm is the amount of variation we have in the metastases. They can be as small as single cells in a large area of tissue.

What data do we have available?

There is a total of 220,000 training images and 57,000 testing images.

Based the data, there is a 40/60 balance between positive and negative examples in the training set. A positive label means that there is at least one pixel of tumor tissue in the center region (32 x 32px) of the image. Tumor tissue in the outer region of the patch do not influence the label.

Imports

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Conv2D, MaxPooling2D
from tensorflow.keras.layers import Dense, Dropout, Flatten, Activation
from tensorflow.keras.models import Sequential
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau, ModelCheckpoin
from tensorflow.keras.optimizers import Adam

import os
import cv2

from sklearn.utils import shuffle
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
import itertools
import shutil

from PIL import Image
```

Now lets create the labeled dataframe

In [2]:

```
data = pd.read_csv('../desktop/_labels.csv')
```

Exploratory Data Analysis

In [3]:
```
data.head()
```

Out[3]:

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

In [4]:
```
data.describe()
```

Out[4]:

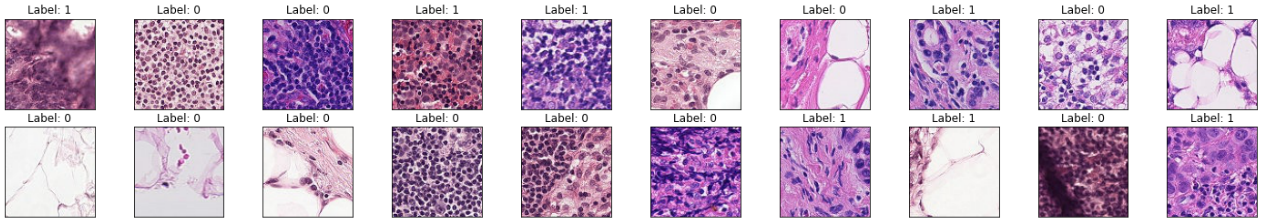
	label
count	220025.000000
mean	0.405031
std	0.490899
min	0.000000
25%	0.000000
50%	0.000000
75%	1.000000
max	1.000000

In [5]:
```
data['label'].value_counts()
```

Out[5]:
```
0    130908
1     89117
Name: label, dtype: int64
```

What do these images look like?

In [6]:
```
fig = plt.figure(figsize=(25, 4))
# display 20 images
train_imgs = os.listdir("../desktop/train")
for idx, img in enumerate(np.random.choice(train_imgs, 20)):
    ax = fig.add_subplot(2, 20//2, idx+1, xticks=[], yticks=[])
    im = Image.open("../desktop/train/" + img)
    plt.imshow(im)
    lab = data.loc[data['id'] == img.split('.')[0], 'label'].values[0]
    ax.set_title(f'Label: {lab}')
```



In [7]:
```
from glob import glob
```

In [8]:
```
labeled_files = glob('../desktop/train/*.tif')
test_files = glob('../desktop/test/*.tif')
```

In [9]:
```
print("labeled_files size :", len(labeled_files))
print("test_files size :", len(test_files))
```

```
labeled_files size : 220025
test_files size : 57458
```

Next lets see if there are any really dark or light images. We will not necessarily remove these, but it is good information to have

In [10]:
```
from tqdm import tqdm_notebook
```

In [11]:
```
DB_PATH   = r'../desktop/'
TRAIN_DIR = r'../desktop/train/'
TEST_DIR  = r'../desktop/test/'
DIR       = ['train/', 'test/']
```

In [12]:
```
data.id = data.id + '.tif'
```

In [13]:
```
data.dtypes
```

Out[13]:
```
id        object
label      int64
dtype: object
```

In [14]:
```
import os, warnings, random, time, multiprocessing, pickle
from skimage.io import imread
```

In [15]:
```
# # Check for any completely black or white images

dark_th = 10 / 255                               # If no pixel reaches this threshold, im
bright_th = 245 / 255                            # If no pixel is under this threshold, i
too_dark_idx = []
too_bright_idx = []

x_tot = np.zeros(3)
x2_tot = np.zeros(3)
counted_ones = 0
```

```
for i, idx in tqdm_notebook(enumerate(data['id']), 'Computing...(220.025 total files)')
     path = os.path.join(TRAIN_DIR, idx)
     imagearray = imread(path).reshape(-1,3)

     if((imagearray.max() / 255) < dark_th):           # is this too dark
         too_dark_idx.append(idx)
         continue                                      # do not include in statistics

     if((imagearray.min() / 255) > bright_th):         # is this too bright
         too_bright_idx.append(idx)
         continue                                      # do not include in statistics

print('There was {0} extremely dark image'.format(len(too_dark_idx)))
print('and {0} extremely bright images'.format(len(too_bright_idx)))
print('Dark one:')
print(too_dark_idx)
print('Bright ones:')
print(too_bright_idx)
```

```
<ipython-input-15-2458ff264092>:12: TqdmDeprecationWarning: This function will be remove
d in tqdm==5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for i, idx in tqdm_notebook(enumerate(data['id']), 'Computing...(220.025 total file
s)'):

There was 1 extremely dark image
and 6 extremely bright images
Dark one:
['9369c7278ec8bcc6c880d99194de09fc2bd4efbe.tif']
Bright ones:
['9071b424ec2e84deeb59b54d2450a6d0172cf701.tif', 'f6f1d771d14f7129a6c3ac2c220d90992c30c1
0b.tif', '5f30d325d895d873d3e72a82ffc0101c45cba4a8.tif', '54df3640d17119486e5c5f98019d2a
92736feabc.tif', '5a268c0241b8510465cb002c4452d63fec71028a.tif', 'c448cd6574108cf14514ad
5bc27c0b2c97fc1a83.tif']
```

It looks like this only consists of 7 images. One that is too dark and another 6 that are too light. Let's visualize these now.

In [16]:

```
unusable = too_dark_idx + too_bright_idx

plt.figure(figsize=(10,10))
i = 0
for n in unusable:
    img = imread(TRAIN_DIR + n)
    plt.subplot(6,6,i+1)
    plt.imshow(img)
    plt.axis('off')
    i = i+1
    plt.tight_layout()
plt.show()
```

Based on the sheer size of the dataset, it is probably not worth taking these outliers out. They should have no change on the performance of the model.

Splitting into training and testing set

In [15]:
```
base_tile_dir = '../desktop/train/'
df = pd.DataFrame({'path': glob(os.path.join(base_tile_dir,'*.tif'))})
```

In [16]:
```
labels = pd.read_csv("../desktop/_labels.csv")
```

In [17]:
```
df['id'] = df.path.map(lambda x: ((x.split("/")[2].split('.')[0])[6:]))
```

In [18]:
```
df
```

Out[18]:

	path	id
0	../desktop/train\00001b2b5609af42ab0ab276dd4cd...	00001b2b5609af42ab0ab276dd4cd41c3e7745b5
1	../desktop/train\000020de2aa6193f4c160e398a8ed...	000020de2aa6193f4c160e398a8edea95b1da598
2	../desktop/train\00004aab08381d25d315384d646f5...	00004aab08381d25d315384d646f5ce413ea24b1
3	../desktop/train\0000d563d5cfafc4e68acb7c98292...	0000d563d5cfafc4e68acb7c9829258a298d9b6a
4	../desktop/train\0000da768d06b879e5754c43e2298...	0000da768d06b879e5754c43e2298ce48726f722
...	...	...
220020	../desktop/train\fffe6c73afcf5f5da5818fb70cb72...	fffe6c73afcf5f5da5818fb70cb723026b172eca
220021	../desktop/train\fffeb3f5361ea57e728fb689e6be3...	fffeb3f5361ea57e728fb689e6be34d07d16ca7e
220022	../desktop/train\fffeca85b16452a7709d163e05a70...	fffeca85b16452a7709d163e05a70e646782b3cc
220023	../desktop/train\fffeeb1297fd4e26f247af648a2a6...	fffeeb1297fd4e26f247af648a2a6f942dfa2e9d
220024	../desktop/train\ffffe55093358954f38bba4c35b6a...	ffffe55093358954f38bba4c35b6aa0ece86177c

220025 rows × 2 columns

In [19]:
```
df = df.merge(labels, on = "id")
```

In [20]:

```
df
```

Out[20]:

	path	id	la
0	../desktop/train\00001b2b5609af42ab0ab276dd4cd...	00001b2b5609af42ab0ab276dd4cd41c3e7745b5	
1	../desktop/train\000020de2aa6193f4c160e398a8ed...	000020de2aa6193f4c160e398a8edea95b1da598	
2	../desktop/train\00004aab08381d25d315384d646f5...	00004aab08381d25d315384d646f5ce413ea24b1	
3	../desktop/train\0000d563d5cfafc4e68acb7c98292...	0000d563d5cfafc4e68acb7c9829258a298d9b6a	
4	../desktop/train\0000da768d06b879e5754c43e2298...	0000da768d06b879e5754c43e2298ce48726f722	
...	...	...	
220020	../desktop/train\fffe6c73afcf5f5da5818fb70cb72...	fffe6c73afcf5f5da5818fb70cb723026b172eca	
220021	../desktop/train\fffeb3f5361ea57e728fb689e6be3...	fffeb3f5361ea57e728fb689e6be34d07d16ca7e	
220022	../desktop/train\fffeca85b16452a7709d163e05a70...	fffeca85b16452a7709d163e05a70e646782b3cc	
220023	../desktop/train\fffeeb1297fd4e26f247af648a2a6...	fffeeb1297fd4e26f247af648a2a6f942dfa2e9d	
220024	../desktop/train\ffffe55093358954f38bba4c35b6a...	ffffe55093358954f38bba4c35b6aa0ece86177c	

220025 rows × 3 columns

In [21]:

```
# taking 10000 sample so our model run faster (experimentation)
from sklearn.model_selection import train_test_split
df_new = df.sample(n=10000, random_state=2018)
train, valid = train_test_split(df_new,test_size=0.2)
```

In [22]:

```
# taking 120000 sample for our ResNet Model
from sklearn.model_selection import train_test_split
df_new = df.sample(n=120000, random_state=2018)
train1, valid1 = train_test_split(df_new,test_size=0.2)
```

In [23]:

```
train
```

Out[23]:

	path	id	lal
63745	../desktop/train\4a86f2cb6bf3f7eb4d3c22e9962f6...	4a86f2cb6bf3f7eb4d3c22e9962f6705fcf125ab	
113762	../desktop/train\84b43635c43104576f58c061b22fb...	84b43635c43104576f58c061b22fb3e413cada77	
83592	../desktop/train\619527f6891c9cfbc9070f6f1d8ac...	619527f6891c9cfbc9070f6f1d8ac79be64be1e1	
198142	../desktop/train\e6b3a6d6630234134447b9cf6df70...	e6b3a6d6630234134447b9cf6df705154a574498	

	path	id	lal
159498	../desktop/train\b9f830f9f789748cbe3d83b56e69b...	b9f830f9f789748cbe3d83b56e69bcb1ee019327	
...	...	...	
30384	../desktop/train\239e6c7942452a45d1ee37ffd5e66...	239e6c7942452a45d1ee37ffd5e6640ba0d591e3	
177767	../desktop/train\cf36e5f1f58d344d1f3ee72f56df3...	cf36e5f1f58d344d1f3ee72f56df3276debefc3d	
62660	../desktop/train\493fdc7cf4cc656809a8ad11179e4...	493fdc7cf4cc656809a8ad11179e4a0199ff39a8	
184145	../desktop/train\d690c3c799dd7128c4bd4c77c5e33...	d690c3c799dd7128c4bd4c77c5e3311b0778f15d	
41805	../desktop/train\30f6745516f3d124e6d70ad26e0b3...	30f6745516f3d124e6d70ad26e0b3a1a769415a0	

8000 rows × 3 columns

In [24]:
```
train['label'].value_counts()
```

Out[24]:
```
0    4771
1    3229
Name: label, dtype: int64
```

In [25]:
```
train['label'] = train['label'].astype('str')
```

In [26]:
```
valid['label'] = valid['label'].astype('str')
```

In [27]:
```
train1
```

Out[27]:

	path	id	la
197318	../desktop/train\e5c79d989cd559229a3505cc7b16a...	e5c79d989cd559229a3505cc7b16a8f7b68b659c	
5619	../desktop/train\06867d46fa0c930dfd3697a3cbe38...	06867d46fa0c930dfd3697a3cbe38480ae8b3018	
37761	../desktop/train\2c32dddf036273dd3be18de93df4e...	2c32dddf036273dd3be18de93df4e3df1133735d	
212070	../desktop/train\f6b6ac6aaae3373652c279849c4fa...	f6b6ac6aaae3373652c279849c4fa94904a9599c	
154913	../desktop/train\b48170c193d8833f948eb1821fcd6...	b48170c193d8833f948eb1821fcd68fcb864ec5d	
...	...	...	
97886	../desktop/train\726ab3fb4a5a4f378dd0b5645df97...	726ab3fb4a5a4f378dd0b5645df977163f4b6eb2	
90046	../desktop/train\692dbb6d50835bfc09449b049a182...	692dbb6d50835bfc09449b049a1828e6815bd572	
43180	../desktop/train\32827279d450664c2a21b53794483...	32827279d450664c2a21b53794483b69d4d8a301	
137380	../desktop/train\a0004fc1b8a1469913349b5a03b06...	a0004fc1b8a1469913349b5a03b0663222edbde3	
7759	../desktop/train\091cac17ce8cd252e6a2633200937...	091cac17ce8cd252e6a26332009377947e88b495	

96000 rows × 3 columns

In [29]:
```
train1['label'].value_counts()
```

Out[29]:
```
0    57165
1    38835
Name: label, dtype: int64
```

In [30]:
```
train1['label'] = train1['label'].astype('str')
```

```
<ipython-input-30-08adb2d9968f>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
guide/indexing.html#returning-a-view-versus-a-copy
  train1['label'] = train1['label'].astype('str')
```

In [31]:
```
valid1['label'] = valid1['label'].astype('str')
```

```
<ipython-input-31-39b55f0e327f>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
guide/indexing.html#returning-a-view-versus-a-copy
  valid1['label'] = valid1['label'].astype('str')
```

In [32]:
```
datagen = ImageDataGenerator(rescale=1.0/255)
```

In [33]:
```
train_generator = datagen.flow_from_dataframe(dataframe = train,
                                                    directory = None,
                                                    x_col = 'path',
                                                    y_col = 'label',
                                                    target_size = (96,96),
                                                    class_mode = "binary",
                                                    batch_size=32,
                                                    seed = 110318,
                                                    shuffle = True)
```

```
Found 8000 validated image filenames belonging to 2 classes.
```

In [34]:
```
valid_generator = datagen.flow_from_dataframe(dataframe = valid,
                                                   directory = None,
                                                   x_col = 'path',
                                                   y_col = 'label',
                                                   target_size = (96,96),
                                                   class_mode = 'binary',
                                                   batch_size = 32,
                                                   shuffle = False)
```

```
Found 2000 validated image filenames belonging to 2 classes.
```

In [35]:
```
train_generator1 = datagen.flow_from_dataframe(dataframe = train1,
                                                    directory = None,
                                                    x_col = 'path',
```

```
                                                 y_col = 'label',
                                                 target_size = (96,96),
                                                 class_mode = "binary",
                                                 batch_size=32,
                                                 seed = 110318,
                                                 shuffle = True)
```

```
Found 96000 validated image filenames belonging to 2 classes.
```

In [36]:

```
valid_generator1 = datagen.flow_from_dataframe(dataframe = valid1,
                                                directory = None,
                                                x_col = 'path',
                                                y_col = 'label',
                                                target_size = (96,96),
                                                class_mode = 'binary',
                                                batch_size = 32,
                                                shuffle = False)
```

```
Found 24000 validated image filenames belonging to 2 classes.
```

EDA Conclusions

Our data really did not need much done to it in terms of cleaning and preprocessing. The positive to negative ratio was left untouched, because although there were more negatives than positives, this is reflective of a real world population. We were also able to see what a negative and positive image actually looked like. Truthfully, to the naked eye it was very hard to tell the difference. Lastly we were able to detect a few outliers and split our training data into a training set and validation set.

Model Architecture

What model architecture are we using and why?

We will be using the ResNet CNN model as our official model, but are also using a manually made simple 3 filter CNN as a baseline model to compare to. The trainable parameters for the simpler model are 1.6 million and for the ResNet 28.3 million parameters. The ResNet model is a relatively new model that overcame the vanishing gradient problem. This had been a major issue in the past with deep neural networks. As mentioned in class, the ResNet avoids this by introducing the identity shortcut connection that can skip one or more layers. We will be compiling using the 'adam' optimizer, because of its success rate on noisy data as compared to stochastic gradient descent. For both the baseline algorithm and ResNet CNN I will be implementing early stopping that will monitor validation loss as well as "reduce lr" that will help to adjust the learning rate as the learning progresses. This is an extremely complex and large dataset, so I believe the ResNet will prove far superior.

In [37]:

```
import tensorflow as tf
from tensorflow.python.keras import Sequential
from tensorflow.keras import layers, optimizers
from tensorflow.keras.layers import *
from tensorflow.keras.models import Model
from tensorflow.keras.initializers import glorot_uniform
from tensorflow.keras.utils import plot_model
from tensorflow.keras.callbacks import ReduceLROnPlateau, EarlyStopping, ModelCheckpoin
```

```
import tensorflow.keras.backend as K
from keras.layers import Input
```

In [38]:

```
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten, BatchNormalization, Activation
from keras.layers import Conv2D, MaxPool2D
```

In [43]:

```
kernel_size = (3,3)
pool_size= (2,2)
first_filters = 32
second_filters = 64
third_filters = 128

dropout_conv = 0.3
dropout_dense = 0.3


model = Sequential()
model.add(Conv2D(first_filters, kernel_size, activation = 'relu', input_shape = (96, 96
model.add(Conv2D(first_filters, kernel_size, activation = 'relu'))
model.add(Conv2D(first_filters, kernel_size, activation = 'relu'))
model.add(MaxPooling2D(pool_size = pool_size))
model.add(Dropout(dropout_conv))

model.add(Conv2D(second_filters, kernel_size, activation ='relu'))
model.add(Conv2D(second_filters, kernel_size, activation ='relu'))
model.add(Conv2D(second_filters, kernel_size, activation ='relu'))
model.add(MaxPooling2D(pool_size = pool_size))
model.add(Dropout(dropout_conv))

model.add(Conv2D(third_filters, kernel_size, activation ='relu'))
model.add(Conv2D(third_filters, kernel_size, activation ='relu'))
model.add(Conv2D(third_filters, kernel_size, activation ='relu'))
model.add(MaxPooling2D(pool_size = pool_size))
model.add(Dropout(dropout_conv))

model.add(Flatten())
model.add(Dense(256, activation = "relu"))
model.add(Dropout(dropout_dense))
model.add(Dense(1, activation = "softmax"))

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

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_9 (Conv2D)           (None, 94, 94, 32)        896       
                                                                 
 conv2d_10 (Conv2D)          (None, 92, 92, 32)        9248      
                                                                 
 conv2d_11 (Conv2D)          (None, 90, 90, 32)        9248      
                                                                 
 max_pooling2d_3 (MaxPooling  (None, 45, 45, 32)       0         
```

```
 2D)

 dropout_4 (Dropout)         (None, 45, 45, 32)        0

 conv2d_12 (Conv2D)          (None, 43, 43, 64)        18496

 conv2d_13 (Conv2D)          (None, 41, 41, 64)        36928

 conv2d_14 (Conv2D)          (None, 39, 39, 64)        36928

 max_pooling2d_4 (MaxPooling  (None, 19, 19, 64)       0
 2D)

 dropout_5 (Dropout)         (None, 19, 19, 64)        0

 conv2d_15 (Conv2D)          (None, 17, 17, 128)       73856

 conv2d_16 (Conv2D)          (None, 15, 15, 128)       147584

 conv2d_17 (Conv2D)          (None, 13, 13, 128)       147584

 max_pooling2d_5 (MaxPooling  (None, 6, 6, 128)        0
 2D)

 dropout_6 (Dropout)         (None, 6, 6, 128)         0

 flatten_1 (Flatten)         (None, 4608)              0

 dense_2 (Dense)             (None, 256)               1179904

 dropout_7 (Dropout)         (None, 256)               0

 dense_3 (Dense)             (None, 1)                 257

=================================================================
Total params: 1,660,929
Trainable params: 1,660,929
Non-trainable params: 0
_________________________________________________________________
```

In [53]:

```
earlystopping1 = EarlyStopping(monitor='val_loss',
                              mode='min',
                              verbose=1,
                              patience=8
                             )
checkpointer1 = ModelCheckpoint(filepath="clf-resnet-weights.hdf5",
                               verbose=1,
                               save_best_only=True
                              )
reduce_lr1 = ReduceLROnPlateau(monitor='val_loss',
                              mode='min',
                              verbose=1,
                              patience=5,
                              min_delta=0.0001,
                              factor=0.2
                             )
callbacks = [checkpointer1, earlystopping1, reduce_lr1]
```

In [45]:

```
earlystopping = EarlyStopping(monitor='val_loss',
                              mode='min',
                              verbose=1,
```

```
                              patience=15
                             )
checkpointer = ModelCheckpoint(filepath="clf-weights.hdf5",
                               verbose=1,
                               save_best_only=True
                              )
reduce_lr = ReduceLROnPlateau(monitor='val_loss',
                              mode='min',
                              verbose=1,
                              patience=5,
                              min_delta=0.0001,
                              factor=0.2
                             )
callbacks = [checkpointer, earlystopping, reduce_lr]
```

In [46]:

```
h = model.fit(train_generator,
              steps_per_epoch= train_generator.n // train_generator.batch_size,
              epochs = 25,
              validation_data= valid_generator,
              validation_steps= valid_generator.n // valid_generator.batch_size,
              callbacks=[checkpointer, earlystopping])
```

```
Epoch 1/25
250/250 [==============================] - ETA: 0s - loss: 0.6777 - accuracy: 0.4036
Epoch 00001: val_loss improved from inf to 0.66384, saving model to clf-weights.hdf5
250/250 [==============================] - 147s 584ms/step - loss: 0.6777 - accuracy: 0.
4036 - val_loss: 0.6638 - val_accuracy: 0.4234
Epoch 2/25
250/250 [==============================] - ETA: 0s - loss: 0.6758 - accuracy: 0.4036
Epoch 00002: val_loss did not improve from 0.66384
250/250 [==============================] - 149s 596ms/step - loss: 0.6758 - accuracy: 0.
4036 - val_loss: 0.6818 - val_accuracy: 0.4234
Epoch 3/25
250/250 [==============================] - ETA: 0s - loss: 0.6752 - accuracy: 0.4036
Epoch 00003: val_loss did not improve from 0.66384
250/250 [==============================] - 146s 586ms/step - loss: 0.6752 - accuracy: 0.
4036 - val_loss: 0.6821 - val_accuracy: 0.4234
Epoch 4/25
250/250 [==============================] - ETA: 0s - loss: 0.6746 - accuracy: 0.4036
Epoch 00004: val_loss did not improve from 0.66384
250/250 [==============================] - 146s 582ms/step - loss: 0.6746 - accuracy: 0.
4036 - val_loss: 0.6860 - val_accuracy: 0.4234
Epoch 5/25
250/250 [==============================] - ETA: 0s - loss: 0.6755 - accuracy: 0.4036
Epoch 00005: val_loss did not improve from 0.66384
250/250 [==============================] - 149s 596ms/step - loss: 0.6755 - accuracy: 0.
4036 - val_loss: 0.6831 - val_accuracy: 0.4234
Epoch 6/25
250/250 [==============================] - ETA: 0s - loss: 0.6748 - accuracy: 0.4036
Epoch 00006: val_loss did not improve from 0.66384
250/250 [==============================] - 145s 581ms/step - loss: 0.6748 - accuracy: 0.
4036 - val_loss: 0.6834 - val_accuracy: 0.4234
Epoch 7/25
250/250 [==============================] - ETA: 0s - loss: 0.6750 - accuracy: 0.4036
Epoch 00007: val_loss did not improve from 0.66384
250/250 [==============================] - 145s 579ms/step - loss: 0.6750 - accuracy: 0.
4036 - val_loss: 0.6816 - val_accuracy: 0.4234
Epoch 8/25
250/250 [==============================] - ETA: 0s - loss: 0.6750 - accuracy: 0.4036
Epoch 00008: val_loss did not improve from 0.66384
250/250 [==============================] - 145s 581ms/step - loss: 0.6750 - accuracy: 0.
```

```
4036 - val_loss: 0.6828 - val_accuracy: 0.4234
Epoch 9/25
250/250 [==============================] - ETA: 0s - loss: 0.6747 - accuracy: 0.4036
Epoch 00009: val_loss did not improve from 0.66384
250/250 [==============================] - 145s 579ms/step - loss: 0.6747 - accuracy: 0.
4036 - val_loss: 0.6820 - val_accuracy: 0.4234
Epoch 10/25
250/250 [==============================] - ETA: 0s - loss: 0.6747 - accuracy: 0.4036
Epoch 00010: val_loss did not improve from 0.66384
250/250 [==============================] - 146s 582ms/step - loss: 0.6747 - accuracy: 0.
4036 - val_loss: 0.6814 - val_accuracy: 0.4234
Epoch 11/25
250/250 [==============================] - ETA: 0s - loss: 0.6749 - accuracy: 0.4036
Epoch 00011: val_loss did not improve from 0.66384
250/250 [==============================] - 145s 581ms/step - loss: 0.6749 - accuracy: 0.
4036 - val_loss: 0.6830 - val_accuracy: 0.4234
Epoch 12/25
250/250 [==============================] - ETA: 0s - loss: 0.6746 - accuracy: 0.4036
Epoch 00012: val_loss did not improve from 0.66384
250/250 [==============================] - 149s 596ms/step - loss: 0.6746 - accuracy: 0.
4036 - val_loss: 0.6815 - val_accuracy: 0.4234
Epoch 13/25
250/250 [==============================] - ETA: 0s - loss: 0.6747 - accuracy: 0.4036
Epoch 00013: val_loss did not improve from 0.66384
250/250 [==============================] - 148s 593ms/step - loss: 0.6747 - accuracy: 0.
4036 - val_loss: 0.6837 - val_accuracy: 0.4234
Epoch 14/25
250/250 [==============================] - ETA: 0s - loss: 0.6751 - accuracy: 0.4036
Epoch 00014: val_loss did not improve from 0.66384
250/250 [==============================] - 148s 593ms/step - loss: 0.6751 - accuracy: 0.
4036 - val_loss: 0.6819 - val_accuracy: 0.4234
Epoch 15/25
250/250 [==============================] - ETA: 0s - loss: 0.6748 - accuracy: 0.4036
Epoch 00015: val_loss did not improve from 0.66384
250/250 [==============================] - 146s 584ms/step - loss: 0.6748 - accuracy: 0.
4036 - val_loss: 0.6825 - val_accuracy: 0.4234
Epoch 16/25
250/250 [==============================] - ETA: 0s - loss: 0.6746 - accuracy: 0.4036
Epoch 00016: val_loss did not improve from 0.66384
250/250 [==============================] - 146s 585ms/step - loss: 0.6746 - accuracy: 0.
4036 - val_loss: 0.6822 - val_accuracy: 0.4234
Epoch 00016: early stopping
```

In [47]:

```python
from tensorflow.keras.applications.resnet50 import ResNet50
```

In [48]:

```python
dropout_fc = 0.5

conv_base = ResNet50(weights = 'imagenet', include_top = False, input_shape = (96,96,3)

my_model = Sequential()

my_model.add(conv_base)
my_model.add(Flatten())
my_model.add(Dense(256, use_bias=False))
my_model.add(BatchNormalization())
my_model.add(Activation("relu"))
my_model.add(Dropout(dropout_fc))
my_model.add(Dense(1, activation = "sigmoid"))
```

In [49]:

```python
conv_base.Trainable=True
```

```
set_trainable=False
for layer in conv_base.layers:
    if layer.name == 'res5a_branch2a':
        set_trainable = True
    if set_trainable:
        layer.trainable = True
    else:
        layer.trainable = False
```

In [50]:

```
my_model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 resnet50 (Functional)       (None, 3, 3, 2048)        23587712  
                                                                 
 flatten_2 (Flatten)         (None, 18432)             0         
                                                                 
 dense_4 (Dense)             (None, 256)               4718592   
                                                                 
 batch_normalization (BatchN  (None, 256)              1024      
 ormalization)                                                   
                                                                 
 activation (Activation)     (None, 256)               0         
                                                                 
 dropout_8 (Dropout)         (None, 256)               0         
                                                                 
 dense_5 (Dense)             (None, 1)                 257       
                                                                 
=================================================================
Total params: 28,307,585
Trainable params: 4,719,361
Non-trainable params: 23,588,224
_________________________________________________________________
```

In [51]:

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

In [54]:

```
z = my_model.fit(train_generator1,
              steps_per_epoch= train_generator1.n // train_generator1.batch_size,
              epochs = 25,
              validation_data= valid_generator1,
              validation_steps= valid_generator1.n // valid_generator1.batch_size,
              callbacks=[checkpointer1, earlystopping1])
```

```
Epoch 1/25
3000/3000 [==============================] - ETA: 0s - loss: 0.5289 - accuracy: 0.7424
Epoch 00001: val_loss improved from inf to 0.54481, saving model to clf-resnet-weights.h
df5
C:\Users\will.pratt\Documents\temp\lib\site-packages\keras\engine\functional.py:1410: Cu
stomMaskWarning: Custom mask layers require a config and must override get_config. When
loading, the custom mask layer must be passed to the custom_objects argument.
  layer_config = serialize_layer_fn(layer)
3000/3000 [==============================] - 1087s 362ms/step - loss: 0.5289 - accuracy:
0.7424 - val_loss: 0.5448 - val_accuracy: 0.7190
```

```
Epoch 2/25
3000/3000 [==============================] - ETA: 0s - loss: 0.5011 - accuracy: 0.7597
Epoch 00002: val_loss did not improve from 0.54481
3000/3000 [==============================] - 1085s 362ms/step - loss: 0.5011 - accuracy:
0.7597 - val_loss: 0.6542 - val_accuracy: 0.6588
Epoch 3/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4922 - accuracy: 0.7640
Epoch 00003: val_loss did not improve from 0.54481
3000/3000 [==============================] - 1084s 361ms/step - loss: 0.4922 - accuracy:
0.7640 - val_loss: 0.5773 - val_accuracy: 0.7118
Epoch 4/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4858 - accuracy: 0.7695
Epoch 00004: val_loss improved from 0.54481 to 0.47980, saving model to clf-resnet-weigh
ts.hdf5
3000/3000 [==============================] - 1108s 369ms/step - loss: 0.4858 - accuracy:
0.7695 - val_loss: 0.4798 - val_accuracy: 0.7737
Epoch 5/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4808 - accuracy: 0.7717
Epoch 00005: val_loss did not improve from 0.47980
3000/3000 [==============================] - 1093s 364ms/step - loss: 0.4808 - accuracy:
0.7717 - val_loss: 0.5663 - val_accuracy: 0.7082
Epoch 6/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4768 - accuracy: 0.7750
Epoch 00006: val_loss did not improve from 0.47980
3000/3000 [==============================] - 1092s 364ms/step - loss: 0.4768 - accuracy:
0.7750 - val_loss: 0.4853 - val_accuracy: 0.7715
Epoch 7/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4739 - accuracy: 0.7766
Epoch 00007: val_loss did not improve from 0.47980
3000/3000 [==============================] - 1102s 367ms/step - loss: 0.4739 - accuracy:
0.7766 - val_loss: 0.4853 - val_accuracy: 0.7704
Epoch 8/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4695 - accuracy: 0.7793
Epoch 00008: val_loss did not improve from 0.47980
3000/3000 [==============================] - 1103s 368ms/step - loss: 0.4695 - accuracy:
0.7793 - val_loss: 0.5378 - val_accuracy: 0.7287
Epoch 9/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4671 - accuracy: 0.7803
Epoch 00009: val_loss did not improve from 0.47980
3000/3000 [==============================] - 1109s 370ms/step - loss: 0.4671 - accuracy:
0.7803 - val_loss: 0.5106 - val_accuracy: 0.7468
Epoch 10/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4643 - accuracy: 0.7837
Epoch 00010: val_loss did not improve from 0.47980
3000/3000 [==============================] - 1105s 368ms/step - loss: 0.4643 - accuracy:
0.7837 - val_loss: 0.4845 - val_accuracy: 0.7597
Epoch 11/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4624 - accuracy: 0.7844
Epoch 00011: val_loss improved from 0.47980 to 0.46353, saving model to clf-resnet-weigh
ts.hdf5
3000/3000 [==============================] - 1088s 363ms/step - loss: 0.4624 - accuracy:
0.7844 - val_loss: 0.4635 - val_accuracy: 0.7794
Epoch 12/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4602 - accuracy: 0.7851
Epoch 00012: val_loss did not improve from 0.46353
3000/3000 [==============================] - 1086s 362ms/step - loss: 0.4602 - accuracy:
0.7851 - val_loss: 0.5011 - val_accuracy: 0.7586
Epoch 13/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4574 - accuracy: 0.7871
Epoch 00013: val_loss did not improve from 0.46353
3000/3000 [==============================] - 1077s 359ms/step - loss: 0.4574 - accuracy:
0.7871 - val_loss: 0.4695 - val_accuracy: 0.7760
Epoch 14/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4552 - accuracy: 0.7878
Epoch 00014: val_loss improved from 0.46353 to 0.46196, saving model to clf-resnet-weigh
```

```
ts.hdf5
3000/3000 [==============================] - 1068s 356ms/step - loss: 0.4552 - accuracy:
0.7878 - val_loss: 0.4620 - val_accuracy: 0.7790
Epoch 15/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4541 - accuracy: 0.7883
Epoch 00015: val_loss did not improve from 0.46196
3000/3000 [==============================] - 1065s 355ms/step - loss: 0.4541 - accuracy:
0.7883 - val_loss: 0.4666 - val_accuracy: 0.7782
Epoch 16/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4507 - accuracy: 0.7904
Epoch 00016: val_loss did not improve from 0.46196
3000/3000 [==============================] - 1072s 357ms/step - loss: 0.4507 - accuracy:
0.7904 - val_loss: 0.5321 - val_accuracy: 0.7429
Epoch 17/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4503 - accuracy: 0.7917
Epoch 00017: val_loss improved from 0.46196 to 0.46075, saving model to clf-resnet-weigh
ts.hdf5
3000/3000 [==============================] - 1070s 357ms/step - loss: 0.4503 - accuracy:
0.7917 - val_loss: 0.4608 - val_accuracy: 0.7805
Epoch 18/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4476 - accuracy: 0.7921
Epoch 00018: val_loss did not improve from 0.46075
3000/3000 [==============================] - 1060s 353ms/step - loss: 0.4476 - accuracy:
0.7921 - val_loss: 0.4695 - val_accuracy: 0.7853
Epoch 19/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4470 - accuracy: 0.7936
Epoch 00019: val_loss did not improve from 0.46075
3000/3000 [==============================] - 1059s 353ms/step - loss: 0.4470 - accuracy:
0.7936 - val_loss: 0.4630 - val_accuracy: 0.7842
Epoch 20/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4448 - accuracy: 0.7944
Epoch 00020: val_loss did not improve from 0.46075
3000/3000 [==============================] - 1059s 353ms/step - loss: 0.4448 - accuracy:
0.7944 - val_loss: 0.4782 - val_accuracy: 0.7786
Epoch 21/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4431 - accuracy: 0.7953
Epoch 00021: val_loss did not improve from 0.46075
3000/3000 [==============================] - 1091s 364ms/step - loss: 0.4431 - accuracy:
0.7953 - val_loss: 0.5120 - val_accuracy: 0.7540
Epoch 22/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4415 - accuracy: 0.7977
Epoch 00022: val_loss did not improve from 0.46075
3000/3000 [==============================] - 1091s 364ms/step - loss: 0.4415 - accuracy:
0.7977 - val_loss: 0.4622 - val_accuracy: 0.7852
Epoch 23/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4399 - accuracy: 0.7979
Epoch 00023: val_loss did not improve from 0.46075
3000/3000 [==============================] - 1088s 363ms/step - loss: 0.4399 - accuracy:
0.7979 - val_loss: 0.5059 - val_accuracy: 0.7681
Epoch 24/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4379 - accuracy: 0.8001
Epoch 00024: val_loss did not improve from 0.46075
3000/3000 [==============================] - 1097s 366ms/step - loss: 0.4379 - accuracy:
0.8001 - val_loss: 0.4722 - val_accuracy: 0.7751
Epoch 25/25
3000/3000 [==============================] - ETA: 0s - loss: 0.4372 - accuracy: 0.7996
Epoch 00025: val_loss improved from 0.46075 to 0.45734, saving model to clf-resnet-weigh
ts.hdf5
3000/3000 [==============================] - 1088s 363ms/step - loss: 0.4372 - accuracy:
0.7996 - val_loss: 0.4573 - val_accuracy: 0.7862
```

In [55]:

```
# saving model achitecture in json file
model_json = my_model.to_json()
```

```
with open("clf-resnet-model.json", "w") as json_file:
    json_file.write(model_json)
```

In [56]:

```
z.history.keys()
```

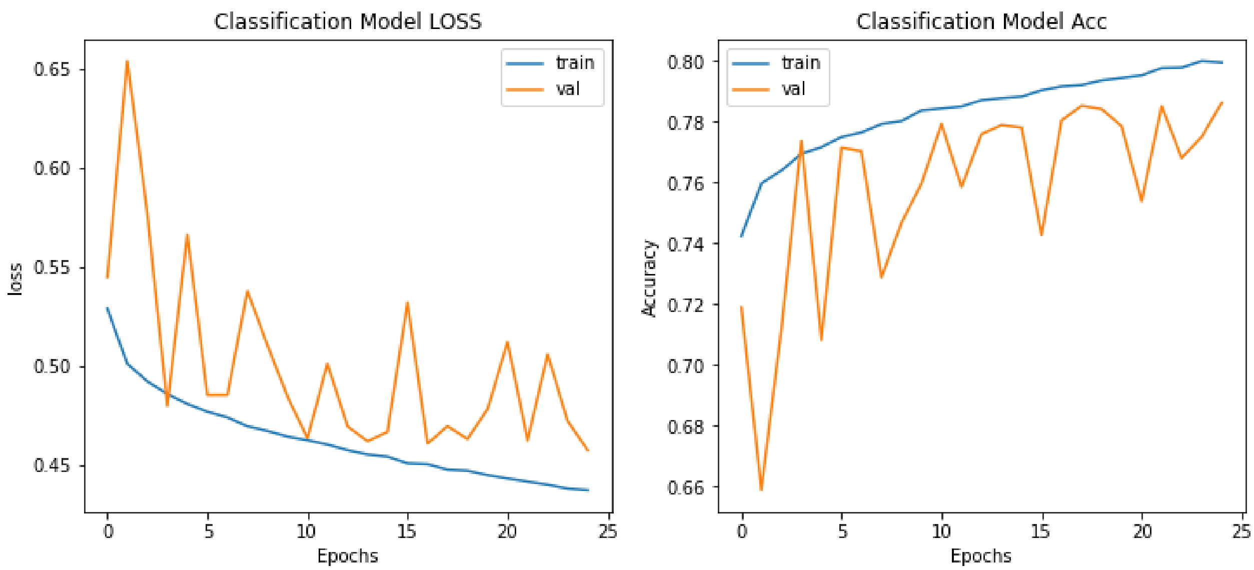
Out[56]:

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

In [57]:

```
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
plt.plot(z.history['loss']);
plt.plot(z.history['val_loss']);
plt.title("Classification Model LOSS");
plt.ylabel("loss");
plt.xlabel("Epochs");
plt.legend(['train', 'val']);

plt.subplot(1,2,2)
plt.plot(z.history['accuracy']);
plt.plot(z.history['val_accuracy']);
plt.title("Classification Model Acc");
plt.ylabel("Accuracy");
plt.xlabel("Epochs");
plt.legend(['train', 'val']);
```



Predictions

In [6]:

```
test_path = '../desktop/test/'
```

In [68]:

```
testdf = pd.DataFrame({'path': glob(os.path.join(test_path, '*.tif'))})
testdf['id'] = testdf.path.map(lambda x: ((x.split("/")[2].split('.')[0])[5:]))
testdf.head(3)
```

Out[68]:

	path	id

	path	id
0	../desktop/test\00006537328c33e284c973d7b39d34...	00006537328c33e284c973d7b39d340809f7271b
1	../desktop/test\0000ec92553fda4ce39889f9226ace...	0000ec92553fda4ce39889f9226ace43cae3364e
2	../desktop/test\00024a6dee61f12f7856b0fc6be20b...	00024a6dee61f12f7856b0fc6be20bc7a48ba3d2

In [26]:

```
with open('clf-resnet-model.json', 'r') as json_file:
    json_savedModel= json_file.read()
#load the model architecture
model1 = tf.keras.models.model_from_json(json_savedModel)
model1.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 resnet50 (Functional)       (None, 3, 3, 2048)        23587712  
                                                                 
 flatten_2 (Flatten)         (None, 18432)             0         
                                                                 
 dense_4 (Dense)             (None, 256)               4718592   
                                                                 
 batch_normalization (BatchN  (None, 256)              1024      
 ormalization)                                                   
                                                                 
 activation (Activation)     (None, 256)               0         
                                                                 
 dropout_8 (Dropout)         (None, 256)               0         
                                                                 
 dense_5 (Dense)             (None, 1)                 257       
                                                                 
=================================================================
Total params: 28,307,585
Trainable params: 4,719,361
Non-trainable params: 23,588,224
_________________________________________________________________
```

In [27]:

```
model1.load_weights('clf-resnet-weights.hdf5')
```

In [28]:

```
model1.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 resnet50 (Functional)       (None, 3, 3, 2048)        23587712  
                                                                 
 flatten_2 (Flatten)         (None, 18432)             0         
                                                                 
 dense_4 (Dense)             (None, 256)               4718592   
                                                                 
 batch_normalization (BatchN  (None, 256)              1024      
 ormalization)                                                   
                                                                 
 activation (Activation)     (None, 256)               0         
                                                                 
 dropout_8 (Dropout)         (None, 256)               0         
```

```
 dense_5 (Dense)             (None, 1)                 257

=================================================================
Total params: 28,307,585
Trainable params: 4,719,361
Non-trainable params: 23,588,224
_________________________________________________________________
```

In [35]:

```
test_df = pd.read_csv('../desktop/sample_submission.csv')

from matplotlib.pyplot import imread
# Kaggle testing
from glob import glob
TESTING_BATCH_SIZE = 64
testing_files = glob(os.path.join('../desktop/test/','*.tif'))
submission = pd.DataFrame()
print(len(testing_files))
for index in range(0, len(testing_files), TESTING_BATCH_SIZE):
    data_frame = pd.DataFrame({'path': testing_files[index:index+TESTING_BATCH_SIZE]})
    data_frame['id'] = data_frame.path.map(lambda x: ((x.split("/")[2].split('.')[0])[5
    data_frame['image'] = data_frame['path'].map(imread)
    images = np.stack(data_frame.image, axis=0)
    predicted_labels = [model1.predict(np.expand_dims(image/255.0, axis=0))[0][0] for i
    predictions = np.array(predicted_labels)
    data_frame['label'] = predictions
    submission = pd.concat([submission, data_frame[["id", "label"]]])
    if index % 1000 == 0 :
        print(index/len(testing_files) * 100)
submission.to_csv('submission_new_model.csv', index=False, header=True)
print(submission.head())
```

```
57458
0.0
13.923213477670645
27.84642695534129
41.769640433011936
55.69285391068258
69.61606738835323
83.53928086602387
97.46249434369453
                                          id     label
0  00006537328c33e284c973d7b39d340809f7271b  0.605574
1  0000ec92553fda4ce39889f9226ace43cae3364e  0.585113
2  00024a6dee61f12f7856b0fc6be20bc7a48ba3d2  0.632934
3  000253dfaa0be9d0d100283b22284ab2f6b643f6  0.731741
4  000270442cc15af719583a8172c87cd2bd9c7746  0.040566
```

In [36]:

```
submission.head(100)
```

Out[36]:

	id	label
0	00006537328c33e284c973d7b39d340809f7271b	0.605574
1	0000ec92553fda4ce39889f9226ace43cae3364e	0.585113
2	00024a6dee61f12f7856b0fc6be20bc7a48ba3d2	0.632934
3	000253dfaa0be9d0d100283b22284ab2f6b643f6	0.731741
4	000270442cc15af719583a8172c87cd2bd9c7746	0.040566

	id	label
...	...	...
31	00694ecfbce48f346cda4d8cffd9a04dcac9e788	0.099596
32	006b80fa929adac3c111bfa47ee8bef69d3195c9	0.542987
33	006deda589bab5b4766d28f762a41e82194bfec7	0.655950
34	006f36c66eed831da677a6d468369095aa6c92f2	0.702060
35	006f9acc85170501cdd0ae43571c97bb9ca62d67	0.259938

100 rows × 2 columns

In [18]:
```
submission.to_csv("submission.csv", index = False, header = True) #create the submissio
```

Results and Analysis

Our models performed relatively as expected. The ResNet CNN performed much better than the baseline one. The ResNet model reached ~80% accuracy on the training set and the baseline reaached only ~41%. Trying a combination of "relu" and sigmoid as the output in the ResNet helped to improve accuracy, after all this is a binary classification problem, which sigmoid is made for. Looking at both the model loss and model accuracy graphs it appears our validation loss and accuracy was quite noisy for all 25 epochs, but did follow a general trend upwards for accuracy and downwards for loss. It could have been beneficial to run more than 25 epochs to continue the trend, but my computer unfortunately does not have a GPU, so the room for error and experimentation was small. Next time I would like to experiment with only 10,000 images using only a single value for the learning rate. The ResNet did well on the unseen test set on Kaggle, with a score of ~84%, surprisingly better than on the training set. For future iterations, performing some form of normalisation on the training and test images could prove to be very worthwhile.

Conclusion

The biggest takeaway I have is that training a CNN requires a lot of experimentation to optimize it. There is no hard and fast way to create the perfect model. There are certainly ways I could have improved accuracy as I mentioned previously, such as normalizing the images (flipping to a certain orientation etc.). Changing activation functions certainly helped performance, as well as adding dense layers. I found the "adam" optimizer also produced the best results. Lastly I would like to have seen a confusion matrix for the test data. The ability to see how many false positives or false negatives would be valuable information to tweaking your model. The reason for that is because when dealing with medical data, in most cases you want to limit the number of false negatives as much as possible. Telling someone they do not have cancer when they do, is much worse than telling someone they do have cancer when they don't. That is the difference between a life being saved.

Sources and Help

I borrowed greatly from these kernels and am grateful for their contributions.

https://www.kaggle.com/code/artgor/simple-eda-and-model-in-pytorch

https://www.kaggle.com/code/praxitelisk/histopathologic-cancer-detection-keras

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