Initial Satelitte Data retrieval

The following dataset was gathered from [NASA FIRMs website (https://firms.modaps.eosdis.nasa.gov/download/)](https://firms.modaps.eosdis.nasa.gov/download/) and encases all fire anomalies between 2015 and 2019 in Northern California. The initial data cleaning that follows will narrow down the scope of our search to Northern California using the proper longitute and latitude ranges comprising a square area of approximately 70,000 km^2. All anomalies contained in the final dataframe should be over land, and also with a confidence rating of over 75%. This confidence rating is a measurement of how sure that the satellite succesfully detected a fire anomaly.

The resulting dataframe we will use to query the Google Static Maps API to retrieve satellite images of areas of northern California that have experienced fires over the last 5 years. We will then try to use these images to train a Convolutional Neural Network that is able to determine if an area has experienced a fire event, or it has not.

Importing Neccesary Libraries and Packages

In [2]:

```
import pandas as pd
import numpy as np

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

import requests
import random

import urllib.request
import warnings
warnings.filterwarnings('ignore')

from tqdm import tqdm
import os
```

The following csv's were downloaded from [https://firms.modaps.eosdis.nasa.gov/country/ (https://firms.modaps.eosdis.nasa.gov/country/)](https://firms.modaps.eosdis.nasa.gov/country/). This archive contains all fire anomalies recorded by the Modis instrument satellites over the planet earth. To get each relevant dataset I merely selected the year, and the country, in this case the United States, in which our target area Northern California is located. Thus each dataset you see below contains all the fire anomalies recorded over the US for each year respective year.

In [3]:

```
df_2015 = pd.read_csv('../data/modis_2015_United_States.csv')
df_2016 = pd.read_csv('../data/modis_2016_United_States.csv')
df_2017 = pd.read_csv('../data/modis_2017_United_States.csv')
df_2018 = pd.read_csv('../data/modis_2018_United_States.csv')
df_2019 = pd.read_csv('../data/modis_2019_United_States.csv')
```

Let's condense all of our dataframes into a single one so we can perform the proper masks in 2 or

3 fell strokes to get the fire instances from our target area.

In [4]:
```
frames = [df_2015, df_2016, df_2017, df_2018, df_2019]
pre_final = pd.concat(frames)
```

In [5]:
```
pre_final.shape
```

Out[5]: (643545, 15)

In [6]:
```
pre_final.head()
```

Out[6]:

	latitude	longitude	brightness	scan	track	acq_date	acq_time	satellite	instrument	conf
0	19.4104	-155.2771	306.4	1.1	1.1	2015-01-01	830	Terra	MODIS	
1	19.4425	-155.0047	324.1	1.1	1.0	2015-01-01	830	Terra	MODIS	
2	19.4601	-154.9925	313.0	1.1	1.0	2015-01-01	830	Terra	MODIS	
3	19.4087	-155.2876	309.8	1.1	1.1	2015-01-01	830	Terra	MODIS	
4	41.6333	-87.1361	301.0	1.9	1.3	2015-01-01	1717	Terra	MODIS	

Data Filtering

The conglorerate dataset above contains all the fire instances across the United Stated between 2015-2019, I wanted to shift my focus to Northern California. Let me show you how I did so.

In [7]:
```
#mask to limit our dataset to latitudes between 38.0881 and 40.8366

pre_final_2 = pre_final[(pre_final['latitude'] >= 38.0881) & (pre_final['lati
```

In [8]:
```
#mask to limit our dataset to longitudes between -123.1208 & -120.2933
pre_final_3 = pre_final_2[(pre_final_2['longitude'] >= -123.1208) & (pre_fina
```

In [9]:
```
#mask to only give us fire instances with a given confidence level from the S
final_wf_df = pre_final_3[(pre_final_3['confidence'] >= 75)]
```

In [10]:
```
final_wf_df.shape
```

Out[10]: (10896, 15)

Our dataset after cleaning has 10,896 images, this should be more than enough instances to feed the model.

In [11]:

```
final_wf_df.head()
```

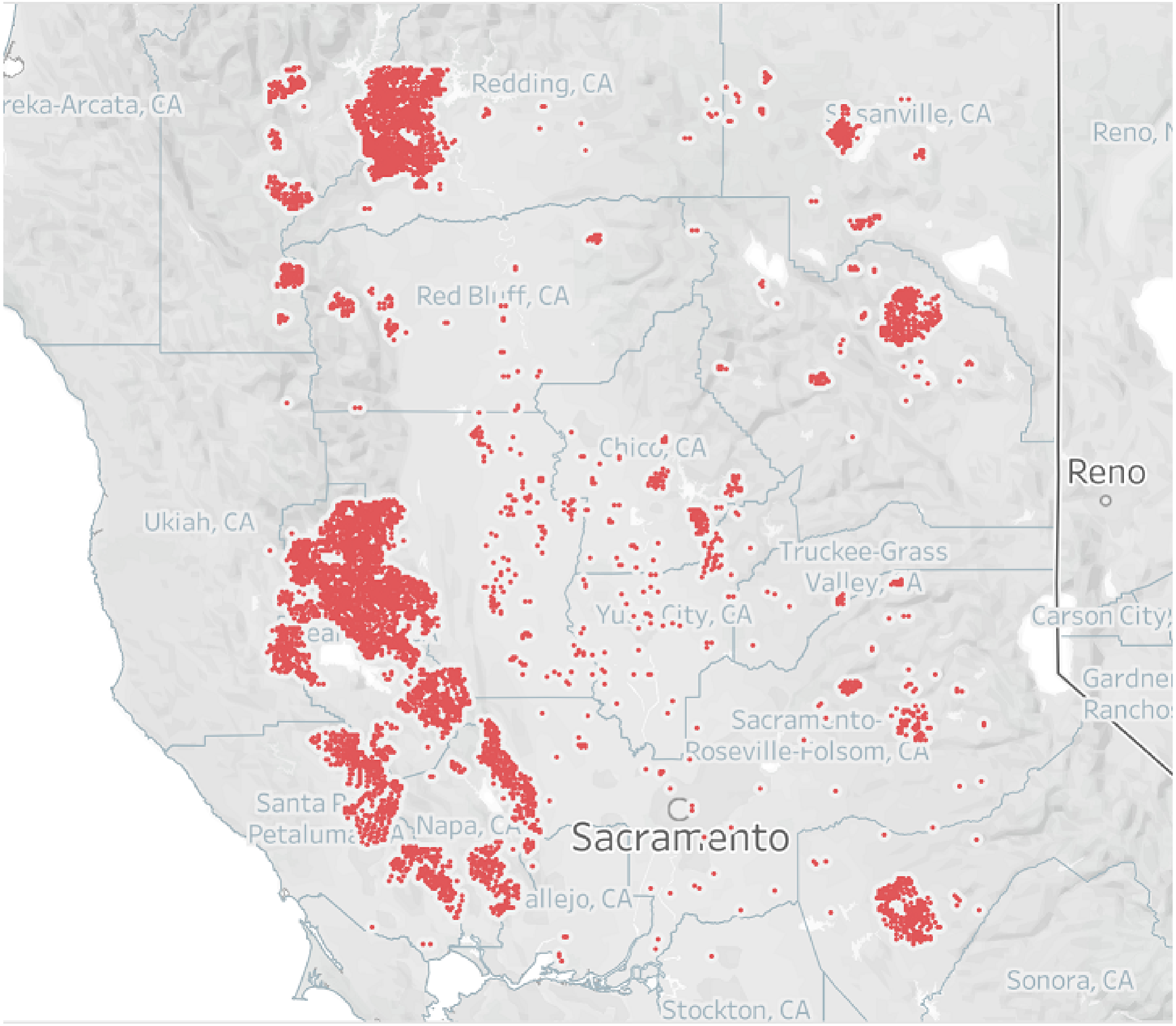
Out[11]:

	latitude	longitude	brightness	scan	track	acq_date	acq_time	satellite	instrument	cc
383	38.8901	-122.9681	322.2	1.3	1.1	2015-01-07	2137	Aqua	MODIS	
384	38.8884	-122.9837	321.4	1.3	1.1	2015-01-07	2137	Aqua	MODIS	
851	39.1576	-120.6349	322.6	3.5	1.8	2015-01-12	2156	Aqua	MODIS	
909	39.9387	-120.7503	327.4	1.1	1.0	2015-01-13	2101	Aqua	MODIS	
911	39.9340	-120.7438	332.2	1.1	1.0	2015-01-13	2101	Aqua	MODIS	

In [12]:

```
final_wf_df.rename(columns={'latitude':'lat',
                            'longitude':'lon',
                            'acq_date':'date'}, inplace = True) #renaming to rec
```

All Fire Instances captured from our cleaned MODIS Thermal Anomaly Data Set.



Setting up for our Google Static Map API Query

Below you will notice I have reduced the final dataframe to include the data, latitude, and longitude components. And then the creation of a new column, centered, which contains a combined tuple of latitude and longitude for a given fire instance. You may also notice when we go to query the google api that an input for the date is not included. This is because the Google static map api does not allow you to retrieve historical satellite images, only its most recent image for the given area queried. At the beginning of this project my intention was to query the NASA Earth API to retrieve historical satellite images of the day of the fire instance. But the images retrieved were problematic and of low resolution, and thus not very valuable when it comes to training a Convolutional Neural Network.

However I have decided to keep the dates of fire instances included for future work when this obstacle is overcome. The corresponding issues of training a CNN model with non historical satellite images for the day of recorded fire instances will be addressed in the attached ReadMe. Also what this means for model interpretability will also be addressed.

In [13]:
```
df_fire_final= final_wf_df[['date','lat','lon']]
```

In [14]:
```
#The data for our columns must be converted to strings for when we go to quer
# our center column is created that creates a combined latitude, longitude tu

df_fire_final['date'] = df_fire_final['date'].astype(str)
df_fire_final['lon'] = df_fire_final['lon'].astype(str)
df_fire_final['lat'] = df_fire_final['lat'].astype(str)
df_fire_final['center']= df_fire_final[['lat','lon']].agg(','.join, axis = 1)
```

In [15]:
```
df_fire_final.head()
```

Out[15]:

	date	lat	lon	center
383	2015-01-07	38.8901	-122.9681	38.8901,-122.9681
384	2015-01-07	38.8884	-122.9837	38.8884,-122.9837
851	2015-01-12	39.1576	-120.6349	39.1576,-120.6349
909	2015-01-13	39.9387	-120.7503	39.9387,-120.7503
911	2015-01-13	39.934	-120.7438	39.934,-120.7438

In [16]:
```
df_fire_final.dtypes #making sure all columns contain object types for we go
```

Out[16]:
```
date      object
lat       object
lon       object
center    object
dtype: object
```

Retrieving Satellite Imagery for Fire-Areas

We now have all the revelant information that we need when we go to retrieve the satellite images of the areas that have experienced fire instances.

Setting up image download request with Google API.

In [17]:
```
img_size = '350x350' #

img_format = 'jpg'

map_scale = '1' # For scale parameter.

maptype = 'satellite' #

zoom = '15'
```

In [18]:
```
key = open('../google_api/google_key.txt', 'r').read() #google api key.
```

In [19]:

```
a = 'https://maps.googleapis.com/maps/api/staticmap?' # Base
b = 'center=' # Center, for our centered longitude and latitude tuple
# Enter df_fire_final['center']
c = '&zoom=' # Zoom
# Enter Zoom
d = '&maptype=satellite' # Map type = satellite imagery

e = '&size=' # Image Size

f = '&key='
# Enter key

# Creating the URL:
url1 = a + b
url2 = c + zoom + d + e + img_size + f + key
```

Looping thru our request

To get all of our images I needed to make a loop that went thru each row of the df_fire_final dataset, and retrieved the centered longitude and latitude tuple to give me the image for a given fire instance. You'll notice that this bar is only halfway completed through. That was more to do with the fact that it costs money to make so many requests through google, and being that this was a replication, it was not worth running thru this entire process again.

In [26]:

```
i = 0
with tqdm(total=df_fire_final.shape[0]) as pbar: #this gives us our progress
                                                     #downloaded all of our im

    for index, row in df_fire_final.iterrows():
        url= url1 + row['center'] + url2
        urllib.request.urlretrieve(url, os.path.join(os.path.pardir,'images',
                                    + row['center']
                                    +'.jpg')
        pbar.update(1)
```

Retrieving the non-fire areas.

To retrieve the latitude and longitude coordinates coordinates for non fire areas I used the df_fire_final dataframe to randomly generate coordinates over the same grid that we pulled our fire area coordinates from. Because there is a good chance we will randomly select non fire areas that are actually fire areas, we are going to go thru later and drop these instances, to avoid duplicates in our training, test, and validation data.

In [20]:

```
non_fire_size= 10000

df_fire_final['lat'] = df_fire_final.lat.astype(float) #to get randomized lat
                                                        #we need to convert b
df_fire_final['lon'] = df_fire_final.lon.astype(float)

new_lat = np.random.uniform(low= min(df_fire_final.lat),
                            high = max(df_fire_final.lat),  #randomizing our
                            size= (non_fire_size,))         # retrieved the w

new_lon = np.random.uniform(low = min(df_fire_final.lon),
                            high = max(df_fire_final.lon),
                            size=(non_fire_size,))

new_coordinates= {'lat':new_lat,'lon':new_lon}

df_non_fire = pd.DataFrame(data = new_coordinates)


df_non_fire['lat'] = df_non_fire['lat'].astype(str)  #converting our new coor
df_non_fire['lon'] = df_non_fire['lon'].astype(str)  #call on our API
df_non_fire['center'] = df_non_fire[['lat', 'lon']].agg(','.join, axis = 1) #
                                                                             #
                                                                             #



df_fire_final['lat'] = df_fire_final.lat.astype(str)
df_fire_final['lon'] = df_fire_final.lon.astype(str)

df_non_fire.head()
```

Out[20]:

	lat	lon	center
0	40.06690741592873	-120.47901350348768	40.06690741592873,-120.47901350348768
1	38.17979820376051	-121.08361211716664	38.17979820376051,-121.08361211716664
2	39.233175090197236	-120.33541678034237	39.233175090197236,-120.33541678034237
3	40.0874595454609	-121.55360363211328	40.0874595454609,-121.55360363211328
4	40.31752714656348	-122.32383252662589	40.31752714656348,-122.32383252662589

In [21]:

```
os.path.join(os.path.pardir,'images','non_fire',) #File path to store our non
```

Out[21]: '..\\images\\non_fire'

Query for non-fire area images

In [ ]:
```
#i = 0
with tqdm(total=df_non_fire.shape[0]) as pbar:

    for index, row in df_non_fire.iterrows():
        url= url1 + row['center'] + url2
        urllib.request.urlretrieve(url, os.path.join(os.path.pardir,'images',
                                        + row['center']
                                        +'.jpg')

        pbar.update(1)
```

Importing Neccesary Packages for modeling

In [22]:
```
import keras
from keras.models import Sequential
from keras.layers import Dense, Conv2D , MaxPool2D , Flatten , Dropout , Batc
from keras.preprocessing.image import ImageDataGenerator
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report,confusion_matrix
from keras.callbacks import ReduceLROnPlateau
import cv2
```

Retrieving images from their respective folders.

Here I'm going to make a function that retrieves fire and non fire class images and labels them according to which folder they reside in the directory. This will later serve to provide a label on the image that the Convolutional Neural Network and train on.

In [23]:
```
labels = ['fire', 'no_fire']
img_size = 150 #here we begin to define our image size as 150 X 150. Pictures


def get_training_data(data_dir):
    data = []
    for label in labels:
        path = os.path.join(data_dir, label)
        class_num = labels.index(label)
        for img in os.listdir(path):
            try:
                img_arr = cv2.imread(os.path.join(path, img))
                resized_arr = cv2.resize(img_arr, (img_size, img_size)) # Res
                data.append([resized_arr, class_num])
            except Exception as e:
                print(e)
    return np.array(data)
```

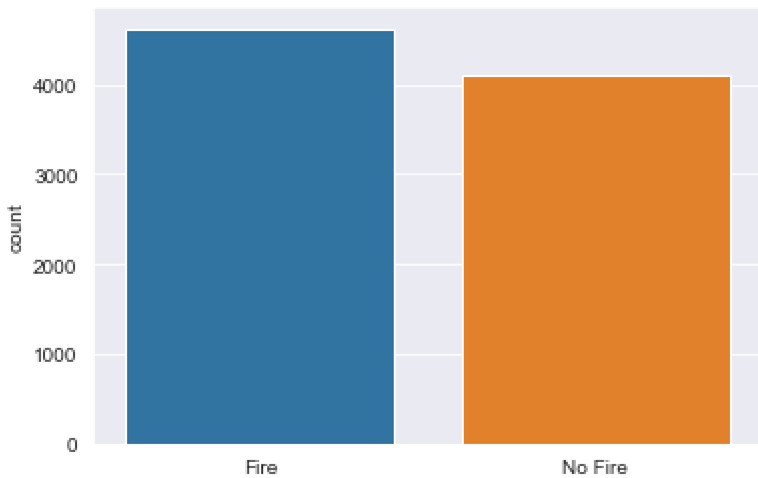
It should be noted that the variables below each contain a list of images. These images had to be split into train, test, and validation folders respectively. It was done the old fashion way...Dragging and Dropping. Respective ratios were honored when it came to how many images were kept to be kept in a given folder type.

In [24]:
```
train = get_training_data('../images/wf_images/train')
test = get_training_data('../images/wf_images/test')
val = get_training_data('../images/wf_images/val')
```

Classification balance for training data.

In [28]:
```
classification_check = []
for i in train:
    if(i[1]==0):
        classification_check.append('Fire')
    else:
        classification_check.append('No Fire')
sns.set_style('darkgrid')
sns.countplot(classification_check)
```

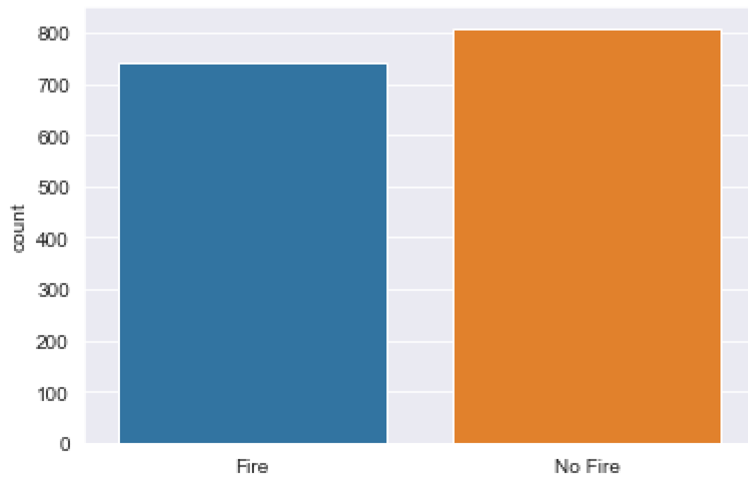
Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x1fe1fbc7160>



Classification Balance for validation data.

In [29]:
```
class_check_2 = []
for i in val:
    if(i[1]==0):
        class_check_2.append('Fire')
    else:
        class_check_2.append('No Fire')
sns.set_style('darkgrid')
sns.countplot(class_check_2)
```

Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x1fe566ba820>



Example of fire-area vs. non-fire area.

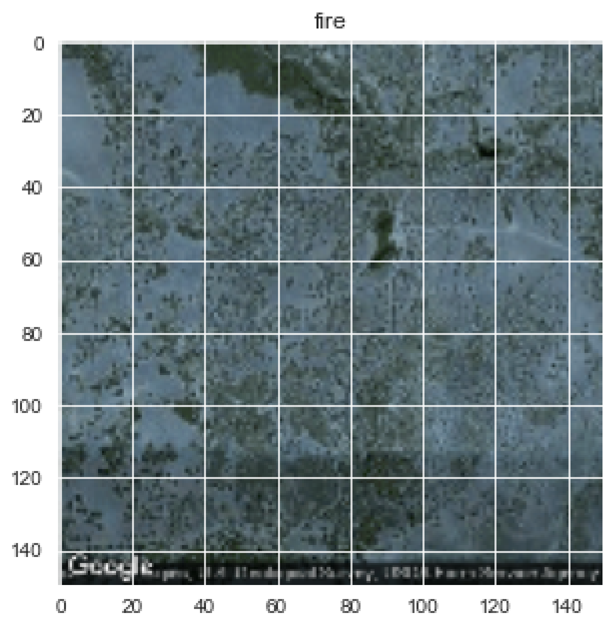
In [30]:

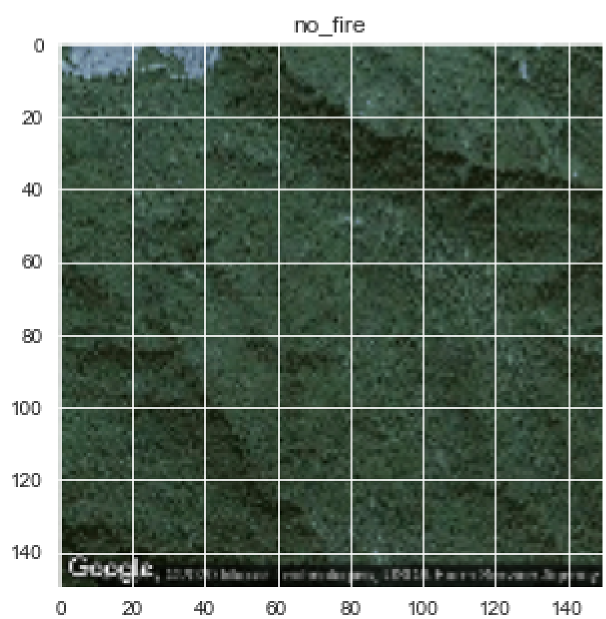
```
plt.figure(figsize = (5,5))
plt.imshow(train[0][0])
plt.title(labels[train[0][1]])

plt.figure(figsize = (5,5))
plt.imshow(train[-1][0])
plt.title(labels[train[-1][1]])
```

Out[30]:

```
Text(0.5, 1.0, 'no_fire')
```





Data Preprocessing

Next we need to go thru each respective folder and make sure that each image has the appropriate fire area or non-fire area class label attached to it. Next I went thru each data array and normalized the RGB image values to range from 0-1. This helps when we are running the

Convolutional Neural Network, and ensure that the model will converge faster. Lastly I reshaped the array so it could be properly pushed through the Convolutional Neural Network.

Step 1.) Image Labeling

In [31]:
```
x_train = []
y_train = []

x_val = []
y_val = []

x_test = []
y_test = []

for feature, label in train:
    x_train.append(feature)
    y_train.append(label)

for feature, label in test:
    x_test.append(feature)
    y_test.append(label)

for feature, label in val:
    x_val.append(feature)
    y_val.append(label)
```

Step 2.) Normalizing the Data

In [32]:
```
# Normalize the data
x_train = np.array(x_train) / 255
x_val = np.array(x_val) / 255
x_test = np.array(x_test) / 255
```

Step 3.) Reshaping the Data

In [33]:
```
# reshaping data array for deep learning
x_train = x_train.reshape(-1, img_size, img_size, 3)
y_train = np.array(y_train)

x_val = x_val.reshape(-1, img_size, img_size, 3)
y_val = np.array(y_val)

x_test = x_test.reshape(-1, img_size, img_size, 3)
y_test = np.array(y_test)
```

The Convolutional Neural Network

For my image classification I decided to use a Convolutional Neural Network. It has an input layer, followed by several convolutional and pooling layers. Each Layer has a relu activation. Relu stands for rectified linear activation function, which is a piecewise linear function that will output the input directly if it is positive, otherwise it will be zero. This prevents our output being stuck between a zero or 1 value. These convolutional and pooling laters converge onto a dense layer that connects each input node to each output node. Finally this layer converges onto a single classification neuron that is sigmoid activated. Sigmoid activation is used for problems like ours where we are making a binary classification: is the image shown a fire area, or a non-fire area.

In [41]:

```
def model_eval(history):
    pd.DataFrame(history.history).plot(figsize = (12,8))
    plt.grid(True)
    plt.gca().set_ylim(0, 1)
    plt.show
```

First Runner Up

I included this model to show the difficulty in getting good results.

In [43]:

```
model_2 = Sequential()
model_2.add(Conv2D(32, (3,3) , strides =1, padding ='same', activation = 'rel
model_2.add(MaxPool2D((2,2) , strides =2, padding ='same'))
model_2.add(Conv2D(64, (3,3), strides =1, padding = 'same', activation = 'rel
model_2.add(Dropout(0.1))
model_2.add(MaxPool2D((2,2), strides = 2, padding = 'same'))
model_2.add(Conv2D(64, (3,3), strides =1, padding = 'same', activation = 'rel
model_2.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
model_2.add(Conv2D(128 , (3,3) , strides = 1 , padding = 'same' , activation
model_2.add(Dropout(0.2))
model_2.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
model_2.add(Flatten())
model_2.add(Dense(units = 128 , activation = 'relu'))
model_2.add(Dropout(0.2))
model_2.add(Dense(units = 1 , activation = 'sigmoid'))
model_2.compile(optimizer = "rmsprop" , loss = 'binary_crossentropy' , metric
model_2.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_4 (Conv2D)            (None, 150, 150, 32)      896       
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 75, 75, 32)        0         
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 75, 75, 64)        18496     
_________________________________________________________________
dropout_3 (Dropout)          (None, 75, 75, 64)        0         
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 38, 38, 64)        0         
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 38, 38, 64)        36928     
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 19, 19, 64)        0         
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 19, 19, 128)       73856     
_________________________________________________________________
dropout_4 (Dropout)          (None, 19, 19, 128)       0         
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 10, 10, 128)       0         
_________________________________________________________________
flatten_1 (Flatten)          (None, 12800)             0         
_________________________________________________________________
dense_2 (Dense)              (None, 128)               1638528   
_________________________________________________________________
dropout_5 (Dropout)          (None, 128)               0         
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 129       
=================================================================
Total params: 1,768,833
Trainable params: 1,768,833
Non-trainable params: 0
_________________________________________________________________
```

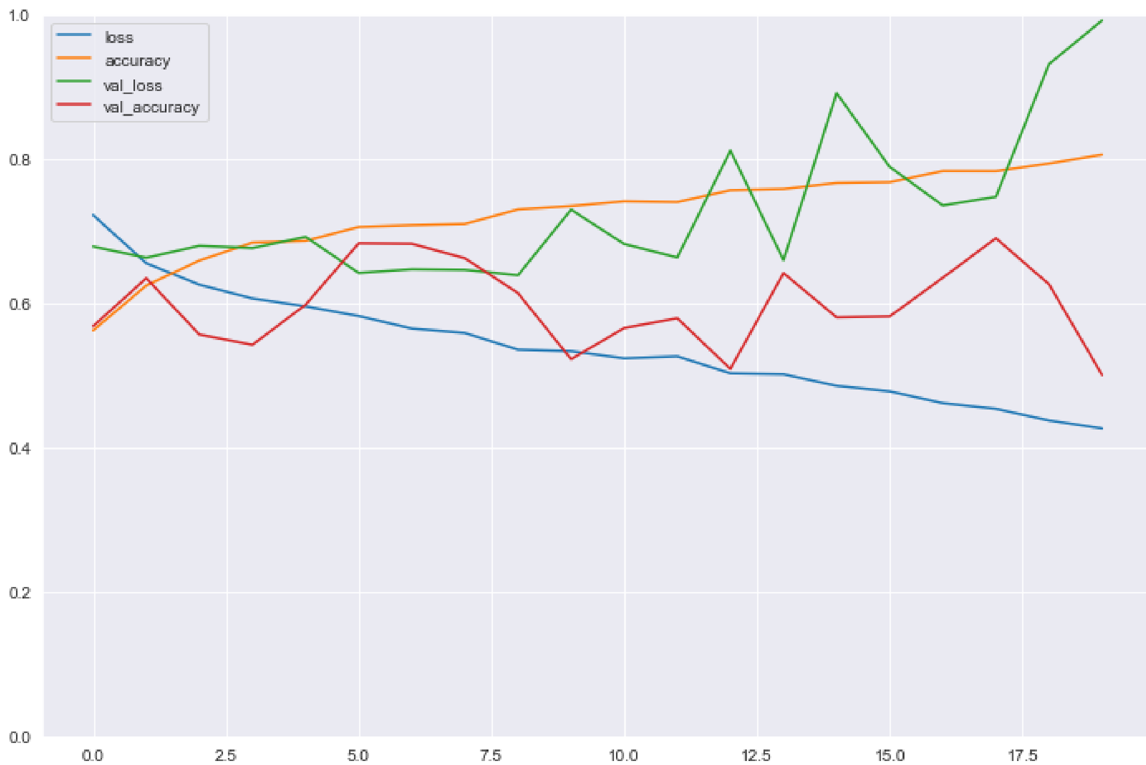
In [45]:
```
history_2= model_2.fit(x_train, y_train, batch_size = 100, epochs= 20, verbos
```

```
Epoch 1/20
88/88 [==============================] - 243s 3s/step - loss: 0.7219 - accu
racy: 0.5622 - val_loss: 0.6782 - val_accuracy: 0.5680
Epoch 2/20
88/88 [==============================] - 255s 3s/step - loss: 0.6552 - accu
racy: 0.6243 - val_loss: 0.6629 - val_accuracy: 0.6344
Epoch 3/20
88/88 [==============================] - 304s 3s/step - loss: 0.6255 - accu
racy: 0.6590 - val_loss: 0.6793 - val_accuracy: 0.5564
Epoch 4/20
88/88 [==============================] - 237s 3s/step - loss: 0.6064 - accu
racy: 0.6837 - val_loss: 0.6762 - val_accuracy: 0.5422
Epoch 5/20
88/88 [==============================] - 228s 3s/step - loss: 0.5954 - accu
racy: 0.6862 - val_loss: 0.6918 - val_accuracy: 0.5977
Epoch 6/20
88/88 [==============================] - 227s 3s/step - loss: 0.5820 - accu
racy: 0.7055 - val_loss: 0.6418 - val_accuracy: 0.6828
Epoch 7/20
88/88 [==============================] - 230s 3s/step - loss: 0.5647 - accu
racy: 0.7080 - val_loss: 0.6469 - val_accuracy: 0.6821
Epoch 8/20
88/88 [==============================] - 224s 3s/step - loss: 0.5586 - accu
racy: 0.7097 - val_loss: 0.6461 - val_accuracy: 0.6622
Epoch 9/20
88/88 [==============================] - 186s 2s/step - loss: 0.5354 - accu
racy: 0.7297 - val_loss: 0.6385 - val_accuracy: 0.6138
Epoch 10/20
88/88 [==============================] - 191s 2s/step - loss: 0.5333 - accu
racy: 0.7344 - val_loss: 0.7295 - val_accuracy: 0.5222
Epoch 11/20
88/88 [==============================] - 184s 2s/step - loss: 0.5234 - accu
racy: 0.7411 - val_loss: 0.6818 - val_accuracy: 0.5654
Epoch 12/20
88/88 [==============================] - 180s 2s/step - loss: 0.5261 - accu
racy: 0.7400 - val_loss: 0.6632 - val_accuracy: 0.5790
Epoch 13/20
88/88 [==============================] - 183s 2s/step - loss: 0.5027 - accu
racy: 0.7564 - val_loss: 0.8114 - val_accuracy: 0.5087
Epoch 14/20
88/88 [==============================] - 179s 2s/step - loss: 0.5014 - accu
racy: 0.7581 - val_loss: 0.6595 - val_accuracy: 0.6415
Epoch 15/20
88/88 [==============================] - 184s 2s/step - loss: 0.4853 - accu
racy: 0.7665 - val_loss: 0.8909 - val_accuracy: 0.5803
Epoch 16/20
88/88 [==============================] - 181s 2s/step - loss: 0.4775 - accu
racy: 0.7676 - val_loss: 0.7887 - val_accuracy: 0.5816
Epoch 17/20
88/88 [==============================] - 182s 2s/step - loss: 0.4613 - accu
racy: 0.7830 - val_loss: 0.7353 - val_accuracy: 0.6351
Epoch 18/20
88/88 [==============================] - 181s 2s/step - loss: 0.4535 - accu
racy: 0.7829 - val_loss: 0.7473 - val_accuracy: 0.6899
Epoch 19/20
```

```
88/88 [==============================] - 181s 2s/step - loss: 0.4374 - accu
racy: 0.7935 - val_loss: 0.9312 - val_accuracy: 0.6260
Epoch 20/20
88/88 [==============================] - 183s 2s/step - loss: 0.4263 - accu
racy: 0.8057 - val_loss: 0.9917 - val_accuracy: 0.5003
```

In [46]:
```
y_preds_2= model_2.predict_classes(x_test)
```

In [48]:
```
model_eval(history_2)
```



Final Model.

In [52]:

```
model_3 = Sequential()
model_3.add(Conv2D(32 , (3,3) , strides = 1 , padding = 'same' , activation =
model_3.add(BatchNormalization())
model_3.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
model_3.add(Conv2D(64 , (3,3) , strides = 1 , padding = 'same' , activation =
model_3.add(Dropout(0.1))
model_3.add(BatchNormalization())
model_3.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
model_3.add(Conv2D(64 , (3,3) , strides = 1 , padding = 'same' , activation =
model_3.add(BatchNormalization())
model_3.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
model_3.add(Conv2D(128 , (3,3) , strides = 1 , padding = 'same' , activation
model_3.add(Dropout(0.2))
model_3.add(BatchNormalization())
model_3.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
model_3.add(Conv2D(256 , (3,3) , strides = 1 , padding = 'same' , activation
model_3.add(Dropout(0.2))
model_3.add(BatchNormalization())
model_3.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
model_3.add(Flatten())
model_3.add(Dense(units = 128 , activation = 'relu'))
model_3.add(Dropout(0.2))
model_3.add(Dense(units = 1 , activation = 'sigmoid'))
model_3.compile(optimizer = "Adam" , loss = 'binary_crossentropy' , metrics =
model_3.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_8 (Conv2D)            (None, 150, 150, 32)      896
_________________________________________________________________
batch_normalization (BatchNo (None, 150, 150, 32)      128
_________________________________________________________________
max_pooling2d_8 (MaxPooling2 (None, 75, 75, 32)        0
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 75, 75, 64)        18496
_________________________________________________________________
dropout_6 (Dropout)          (None, 75, 75, 64)        0
_________________________________________________________________
batch_normalization_1 (Batch (None, 75, 75, 64)        256
_________________________________________________________________
max_pooling2d_9 (MaxPooling2 (None, 38, 38, 64)        0
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 38, 38, 64)        36928
_________________________________________________________________
batch_normalization_2 (Batch (None, 38, 38, 64)        256
_________________________________________________________________
max_pooling2d_10 (MaxPooling (None, 19, 19, 64)        0
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 19, 19, 128)       73856
_________________________________________________________________
dropout_7 (Dropout)          (None, 19, 19, 128)       0
_________________________________________________________________
batch_normalization_3 (Batch (None, 19, 19, 128)       512
_________________________________________________________________
```

```
max_pooling2d_11 (MaxPooling (None, 10, 10, 128)       0
_________________________________________________________________
conv2d_12 (Conv2D)           (None, 10, 10, 256)       295168
_________________________________________________________________
dropout_8 (Dropout)          (None, 10, 10, 256)       0
_________________________________________________________________
batch_normalization_4 (Batch (None, 10, 10, 256)       1024
_________________________________________________________________
max_pooling2d_12 (MaxPooling (None, 5, 5, 256)         0
_________________________________________________________________
flatten_2 (Flatten)          (None, 6400)              0
_________________________________________________________________
dense_4 (Dense)              (None, 128)               819328
_________________________________________________________________
dropout_9 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 129
=================================================================
Total params: 1,246,977
Trainable params: 1,245,889
Non-trainable params: 1,088
_________________________________________________________________
```

With data augmentation to prevent overfitting and handling the imbalance in dataset

In [54]:

```
datagen = ImageDataGenerator(
        featurewise_center=False,  # set input mean to 0 over the dataset
        samplewise_center=False,  # set each sample mean to 0
        featurewise_std_normalization=False,  # divide inputs by std of the d
        samplewise_std_normalization=False,  # divide each input by its std
        zca_whitening=False,  # apply ZCA whitening
        rotation_range = 30,  # randomly rotate images in the range (degrees,
        zoom_range = 0.2, # Randomly zoom image
        width_shift_range=0.1,  # randomly shift images horizontally (fractio
        height_shift_range=0.1,  # randomly shift images vertically (fraction
        horizontal_flip = True,  # randomly flip images
        vertical_flip=False)  # randomly flip images


datagen.fit(x_train)
```

In [55]:

```
learning_rate_reduction = ReduceLROnPlateau(monitor='val_accuracy', patience
```

In [56]:
```
history_3 = model_3.fit(datagen.flow(x_train,y_train, batch_size = 50),
                        epochs = 30 ,
                        validation_data = datagen.flow(x_val, y_val),
                        callbacks = [learning_rate_reduction])
```

```
Epoch 1/30
175/175 [==============================] - 418s 2s/step - loss: 0.6787 - ac
curacy: 0.6994 - val_loss: 0.9698 - val_accuracy: 0.5216
Epoch 2/30
175/175 [==============================] - 411s 2s/step - loss: 0.5581 - ac
curacy: 0.7205 - val_loss: 0.6635 - val_accuracy: 0.5719
Epoch 3/30
175/175 [==============================] - 403s 2s/step - loss: 0.5495 - ac
curacy: 0.7309 - val_loss: 0.5762 - val_accuracy: 0.7228
Epoch 4/30
175/175 [==============================] - 399s 2s/step - loss: 0.5224 - ac
curacy: 0.7428 - val_loss: 0.7311 - val_accuracy: 0.5764
Epoch 5/30
175/175 [==============================] - ETA: 0s - loss: 0.5219 - accurac
y: 0.7468
Epoch 00005: ReduceLROnPlateau reducing learning rate to 0.0003000000142492
354.
175/175 [==============================] - 396s 2s/step - loss: 0.5219 - ac
curacy: 0.7468 - val_loss: 0.7375 - val_accuracy: 0.5545
Epoch 6/30
175/175 [==============================] - 399s 2s/step - loss: 0.4886 - ac
curacy: 0.7649 - val_loss: 0.6871 - val_accuracy: 0.5983
Epoch 7/30
175/175 [==============================] - 397s 2s/step - loss: 0.4848 - ac
curacy: 0.7679 - val_loss: 0.5985 - val_accuracy: 0.7292
Epoch 8/30
175/175 [==============================] - 399s 2s/step - loss: 0.4754 - ac
curacy: 0.7740 - val_loss: 0.7062 - val_accuracy: 0.6422
Epoch 9/30
175/175 [==============================] - ETA: 0s - loss: 0.4734 - accurac
y: 0.7776
Epoch 00009: ReduceLROnPlateau reducing learning rate to 9.000000427477062e
-05.
175/175 [==============================] - 398s 2s/step - loss: 0.4734 - ac
curacy: 0.7776 - val_loss: 0.6214 - val_accuracy: 0.6944
Epoch 10/30
175/175 [==============================] - 399s 2s/step - loss: 0.4571 - ac
curacy: 0.7856 - val_loss: 0.6980 - val_accuracy: 0.6499
Epoch 11/30
175/175 [==============================] - ETA: 0s - loss: 0.4442 - accurac
y: 0.7897
Epoch 00011: ReduceLROnPlateau reducing learning rate to 2.700000040931627e
-05.
175/175 [==============================] - 395s 2s/step - loss: 0.4442 - ac
curacy: 0.7897 - val_loss: 0.9192 - val_accuracy: 0.5764
Epoch 12/30
175/175 [==============================] - 398s 2s/step - loss: 0.4430 - ac
curacy: 0.7910 - val_loss: 0.7777 - val_accuracy: 0.6112
Epoch 13/30
175/175 [==============================] - ETA: 0s - loss: 0.4438 - accurac
y: 0.7893
Epoch 00013: ReduceLROnPlateau reducing learning rate to 8.100000013655517e
```

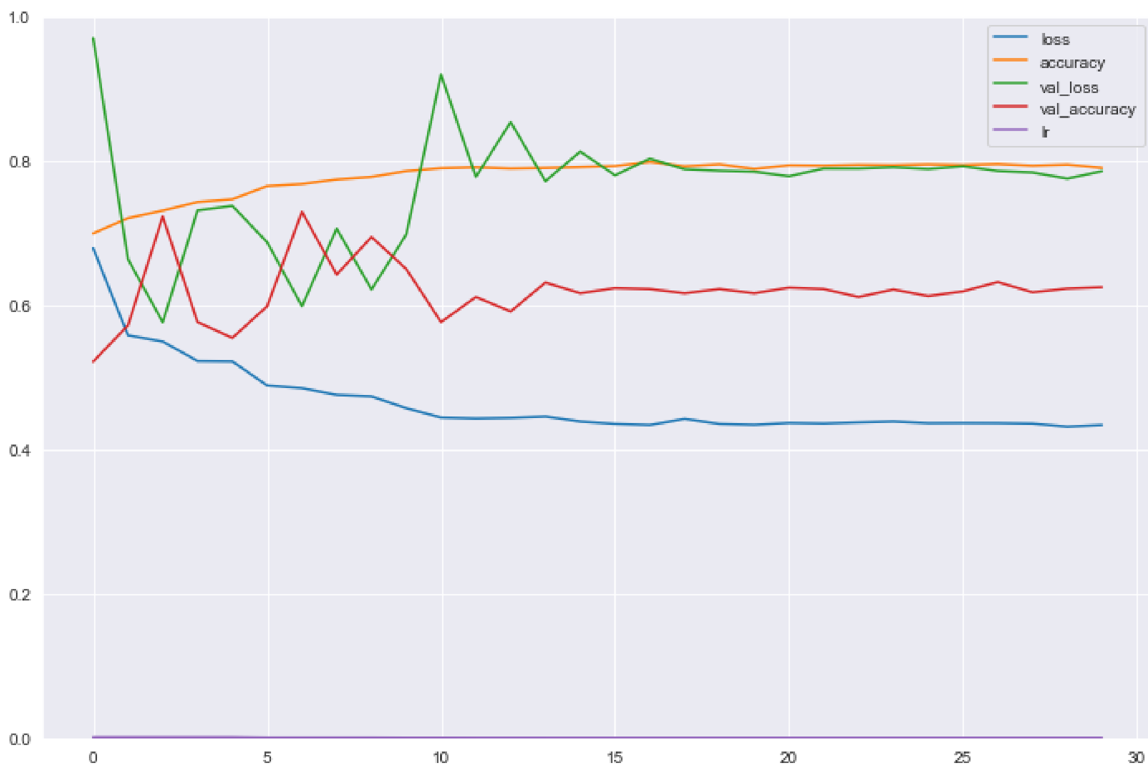
```
-06.
175/175 [==============================] - 398s 2s/step - loss: 0.4438 - ac
curacy: 0.7893 - val_loss: 0.8536 - val_accuracy: 0.5912
Epoch 14/30
175/175 [==============================] - 394s 2s/step - loss: 0.4456 - ac
curacy: 0.7901 - val_loss: 0.7716 - val_accuracy: 0.6312
Epoch 15/30
175/175 [==============================] - ETA: 0s - loss: 0.4387 - accurac
y: 0.7913
Epoch 00015: ReduceLROnPlateau reducing learning rate to 2.429999949526973e
-06.
175/175 [==============================] - 397s 2s/step - loss: 0.4387 - ac
curacy: 0.7913 - val_loss: 0.8128 - val_accuracy: 0.6164
Epoch 16/30
175/175 [==============================] - 398s 2s/step - loss: 0.4354 - ac
curacy: 0.7927 - val_loss: 0.7797 - val_accuracy: 0.6235
Epoch 17/30
175/175 [==============================] - ETA: 0s - loss: 0.4339 - accurac
y: 0.7984
Epoch 00017: ReduceLROnPlateau reducing learning rate to 1e-06.
175/175 [==============================] - 395s 2s/step - loss: 0.4339 - ac
curacy: 0.7984 - val_loss: 0.8030 - val_accuracy: 0.6222
Epoch 18/30
175/175 [==============================] - 397s 2s/step - loss: 0.4424 - ac
curacy: 0.7924 - val_loss: 0.7882 - val_accuracy: 0.6164
Epoch 19/30
175/175 [==============================] - 399s 2s/step - loss: 0.4354 - ac
curacy: 0.7951 - val_loss: 0.7860 - val_accuracy: 0.6222
Epoch 20/30
175/175 [==============================] - 395s 2s/step - loss: 0.4341 - ac
curacy: 0.7887 - val_loss: 0.7848 - val_accuracy: 0.6164
Epoch 21/30
175/175 [==============================] - 400s 2s/step - loss: 0.4368 - ac
curacy: 0.7937 - val_loss: 0.7784 - val_accuracy: 0.6241
Epoch 22/30
175/175 [==============================] - 399s 2s/step - loss: 0.4360 - ac
curacy: 0.7933 - val_loss: 0.7892 - val_accuracy: 0.6222
Epoch 23/30
175/175 [==============================] - 394s 2s/step - loss: 0.4375 - ac
curacy: 0.7943 - val_loss: 0.7892 - val_accuracy: 0.6112
Epoch 24/30
175/175 [==============================] - 397s 2s/step - loss: 0.4388 - ac
curacy: 0.7940 - val_loss: 0.7911 - val_accuracy: 0.6215
Epoch 25/30
175/175 [==============================] - 397s 2s/step - loss: 0.4365 - ac
curacy: 0.7950 - val_loss: 0.7885 - val_accuracy: 0.6125
Epoch 26/30
175/175 [==============================] - 395s 2s/step - loss: 0.4366 - ac
curacy: 0.7942 - val_loss: 0.7924 - val_accuracy: 0.6190
Epoch 27/30
175/175 [==============================] - 396s 2s/step - loss: 0.4365 - ac
curacy: 0.7954 - val_loss: 0.7857 - val_accuracy: 0.6319
Epoch 28/30
175/175 [==============================] - 399s 2s/step - loss: 0.4358 - ac
curacy: 0.7932 - val_loss: 0.7837 - val_accuracy: 0.6177
Epoch 29/30
175/175 [==============================] - 394s 2s/step - loss: 0.4315 - ac
```

```
curacy: 0.7946 - val_loss: 0.7752 - val_accuracy: 0.6228
Epoch 30/30
175/175 [==============================] - 397s 2s/step - loss: 0.4338 - ac
curacy: 0.7902 - val_loss: 0.7855 - val_accuracy: 0.6248
```

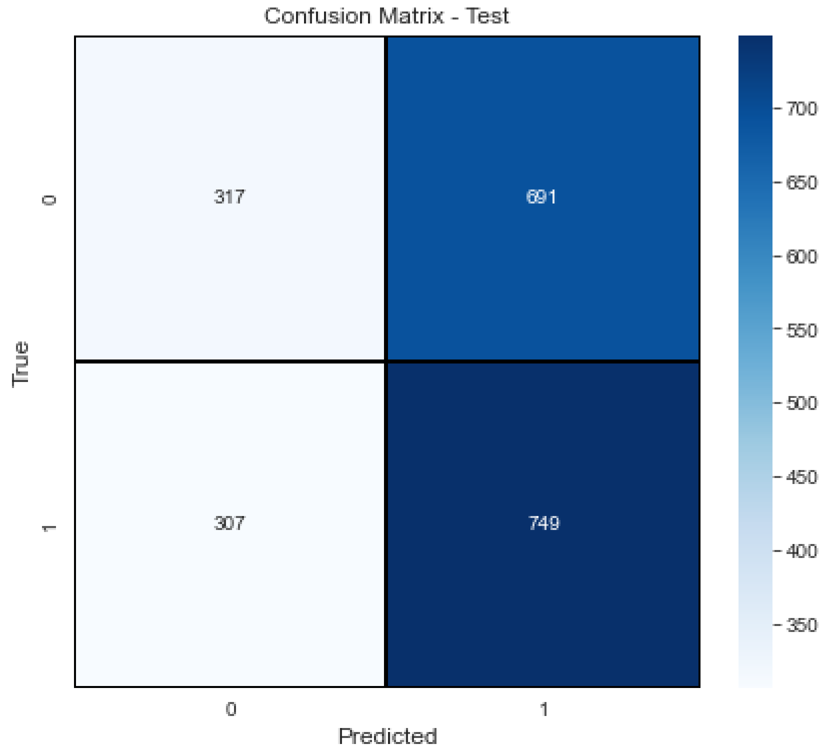
In [57]:
```
conv_model_metrics(model_3)
```

```
273/273 [==============================] - 48s 178ms/step - loss: 0.7231 -
accuracy: 0.6394
65/65 [==============================] - 13s 203ms/step - loss: 1.2906 - ac
curacy: 0.4651
Train loss: 72.307%
Train Accuracy 63.942%
Test Loss: 129.057%
Test Accuracy: 46.512%
```

In [58]:
```
model_eval(history_3)
```



The best model accuracy represented here was approximately 46%. The model was predicting that an area that had experienced a wildfire was about just as likely to have not experienced a wildfire, and vice-versa. Here you can see in the confusion matrix below, in which 0 represents wildfire areas, and 1 represents non-fire areas, that we have an almost perfect balance between false positives to true positives.



As I attempted to make the model more and more complex, the model started to classify most images as non-wild fire areas, most likely due to overfitting and overlapping features between the two types of areas. Eventually at some point 50% accuracy was the best intended target. Other more advanced models that I ran for longer epochs and had more finely tuned hyperparameters saw a degredation in accuracy, and soaring rates of validation loss.

This is most likely due to overfitting and overlapping similiarties betweeen areas that have experienced wildfire events and those that have not. It is also likely that there is not enough information available in raw satellite images for the CNN to train on to make an accurate prediction. This problem, and strategies to overcome it is addressed in the [Final ReadMe (https://github.com/ptanner925/wildfire_capstone/blob/main/README.md)](https://github.com/ptanner925/wildfire_capstone/blob/main/README.md)