Benjamin Luo (6/9/2024)

Problem 1.

Solution.

- 16 neurons are needed to produce the results of the convolutional filter, which in this case is a 4x4 feature map.
- $36 \times 16 + 16 = 594$ parameters needed for the dense layer neural network.
- 10 weight values are needed for the convolutional filter; 9 for the each dimension of the filter, and 1 taking in account for bias.
- Dense networks are designed to find global patterns due to the output being a classification based on every pixel in the image as individual input. On the other hand, the convolutional filter intends to learn and find local patterns, by scanning through the image with convolutional filters, which can be multi-selections in some cases, which is thus designed to train more specific features of an image.

□

Problem 2.

Solution.

$$v = w_1x_1 + w_2x_2 + \cdots + w_9x_9$$

$$v = 1(1)+(-1)(-1)+(-1)(-1)+(-1)(-1)+1(1)+(-1)(-1)+(-1)(-1)+(-1)(-1)+1(1)$$

$$v = 9$$

- The purpose of the weight values in the 3x3 convolutional filter is to look through the image to see if there are patterns like the filter that are present in the image.
- When moving the filter across the image, 66% of the image is preserved between any two movements across one stride (assuming stride = 1).
- The size of the feature map after applying the filter to the whole image is 4x4. The factors that affect the feature map size is the size of the convolutional filter (i.e. 1x1, 3x3, 5x5, etc) as well as stride.

□

Problem 3.

Solution.

Resulting feature map output:

-10	-9	4	1
-2	1	-10	-8

-10	-9	4	1
-2	1	-10	-8

$\Rightarrow$ Result of the 2x2 max pooling $\Rightarrow$

1	4

- The role of the convolutional filter in Table 2 is to identify a specific pattern, a presence of a horizontal line pattern in the image. It achieves this by using a filter to run through the image in order to see what sections of the image respond most strongly to the filter's parameters.

- The 2x2 max pooling layer is then used to reduce the noise and train the relevant neurons towards the pattern outlined by the convolutional filter.

□

Problem 4.

Solution.

- The name of the C1 layer is Convolutional Layer 1; The size of the C1 layer filters is 5x5. Convolutional Layer 1 has $((5 \times 5 \times 1) + 1) \times 6 = 156$ weight values.

- C3 layer's filter size is also 5x5. C3 layer has $((5 \cdot 5 \cdot 6) + 1) \cdot 16 = 2,416$ weight values.

- C5 and F6 have 2,040 and 10,164 weight values, respectively.
  $((1 \cdot 1 \cdot 16) + 1) \cdot 120 = 2,040$
  $(120 \cdot 84) + 84 = 10,164$

□

Problem 5.

Solution. (image of the designed network) □

Problem 6.

Solution.

- GoogleNet has 22 layers; The main difference between GoogleNet and VGG-16 is how the networks are structured. The VGG-16 use a conventional approach, using a combination of convolutional, pooling, and dense layers in a single path. GoogleNet is different from VGG-16 in that GoogleNet has multiple network paths running parallel, using inception networks.

- The motivation of the inception modules lies in the search of being able to capture a more sparse variety of patterns with a deep learning neural network. Inception modules enable this by allowing the network to have multiple parallel running pipelines.

- The purpose of the 1x1 convolutional layers in the inception module is to be able to reduce dimensionality before running the convolutional layers. It has been shown that doing this can drastically reduce the amount of weight parameters if the number of feature arrays can be reduced, which is the purpose of the 1x1 convolutional filters.

- The 2nd convolutional layer has $((1 \cdot 1 \cdot 64) + 1) \cdot 64 = 4,160$ tunable parameters.

- The 3rd convolutional layer has $((3 \cdot 3 \cdot 64) + 1) \cdot 192 = 110,784$ tunable parameters.

- The inception module layer 3(a) is as listed:
  `First path:`
  1×1 conv $\Rightarrow ((7 \cdot 7 \cdot 192) + 1) \cdot 64 = 9409 \cdot 64 = 602,176$
  First path has 602,176 tunable parameters.

  `Second path:`
  1×1 conv $\Rightarrow ((1 \cdot 1 \cdot 192) + 1) \cdot 96 = 193 \cdot 96 = 18,528$
  3×3 conv $\Rightarrow ((3 \cdot 3 \cdot 96) + 1) \cdot 128 = 865 \cdot 128 = 110,720$
  Second path has a total of 129,248 tunable parameters.

  `Third path:`
  1×1 conv $\Rightarrow ((1 \cdot 1 \cdot 192) + 1) \cdot 16 = 193 \cdot 16 = 3,088$
  5×5 conv $\Rightarrow ((5 \cdot 5 \cdot 16) + 1) \cdot 32 = 401 \cdot 32 = 12,832$
  Third path has a total of 13,872 tunable parameters.

  `Fourth path:`
  3×3 maxpool $\Rightarrow 0$
  1×1 conv $\Rightarrow ((1 \cdot 1 \cdot 32) + 1) \cdot 32) = 1,056$
  Fourth path as a total of 1,056 tunable parameters.

- The purpose of the three softwmax outputs at different points in the network is to be able to analyze and assess network result accuracy as we progress through the network; if the classification improve from results earlier in the network compared to results later in the network, we can conclude that the network is improving in accuracy of the classification model.

□

Problem 7.

Solution. See rest of pdf for notebook html output. □

In [ ]:
```
# CAP6619 Deep Learning Summer 2024 - CNNImageClassification.ipynb
# Benjamin Luo
# 6/9/2024
#
# CNN Image Classification
# Dog vs. Cat classification
# Downloaded data from https://www.kaggle.com/c/dogs-vs-cats/data
# For training set, used cat/dog 1-500, 3001-3500
# For test set, used cat/dog 1501-2000, 4000-4499
# For validation set, used cat/dog 1001-1500
```

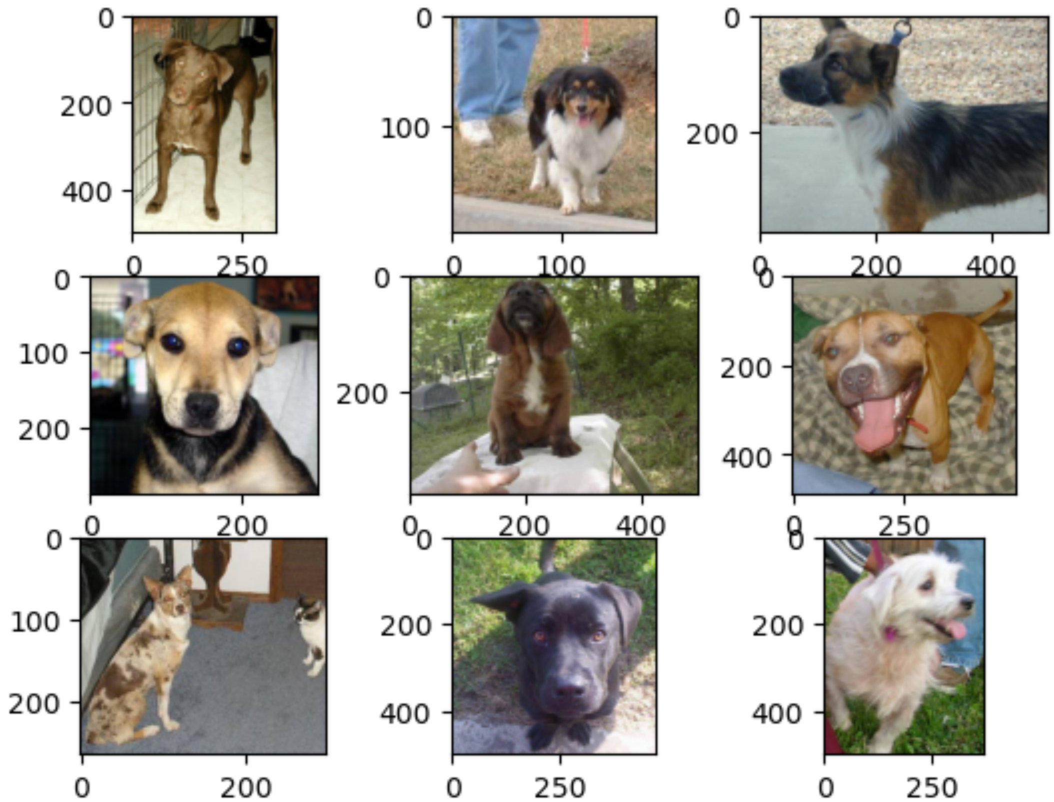
In [ ]:
```
from matplotlib import pyplot as plt
from matplotlib.image import imread
from keras.utils import to_categorical
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Dense, Dropout, Flatten, BatchNormal
from keras.optimizers import SGD
from keras.preprocessing.image import ImageDataGenerator

folder = "dogvscat/"
```

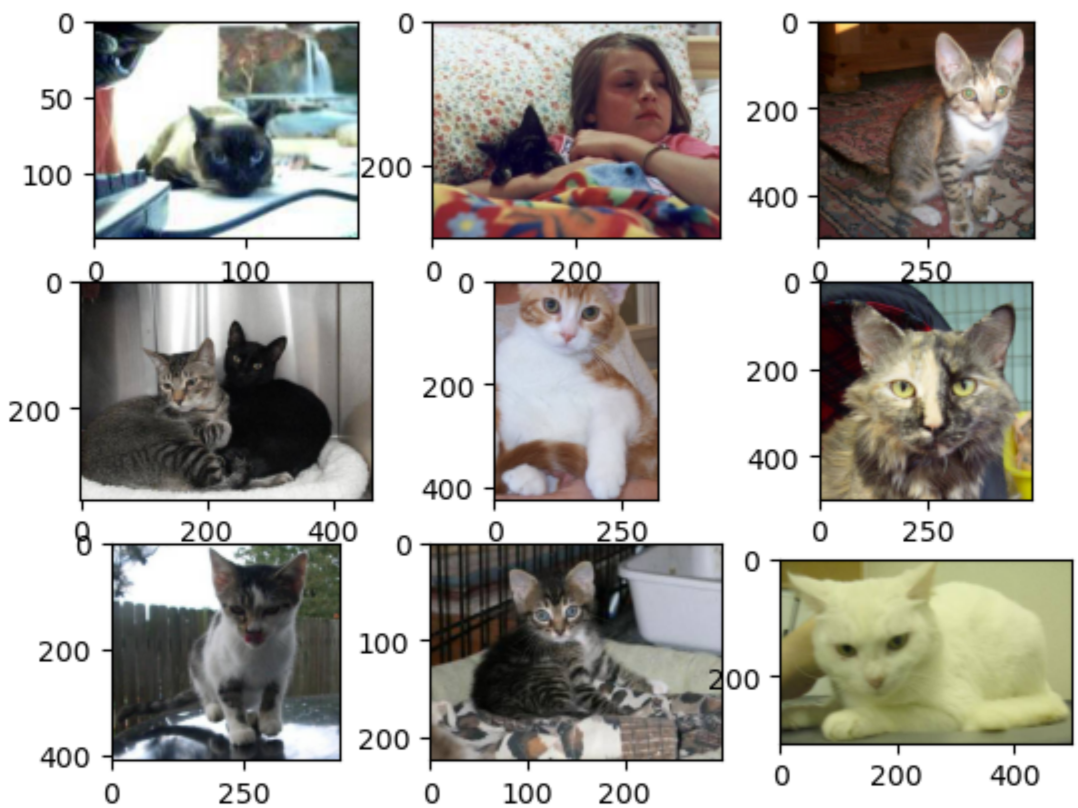
In [ ]:
```
def displayImages(foldername, dogorcat, startID):
    for i in range(9):
        plt.subplot(330+1+i)
        filename = foldername + dogorcat + "." + str(i+startID) + ".jpg"
        image = imread(filename)
        plt.imshow(image)

plt.show()
```

In [ ]:
```
displayImages(folder+"train/dog/", "dog", 1)
```



```
In [ ]: displayImages(folder+"train/cat/", "cat", 5)
```



```
In [ ]: training_data_generator = ImageDataGenerator(
            rotation_range=40,
            width_shift_range=0.2,
```

```
    height_shift_range=0.2,
    rescale=1./255,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest')
validation_data_generator = ImageDataGenerator(rescale=1./255)
test_data_generator = ImageDataGenerator(rescale=1./255)
```

In [ ]:

```
from tensorflow.keras.utils import array_to_img, img_to_array, load_img
img = load_img(folder+'train/dog/dog.1.jpg')
x = img_to_array(img)
x = x.reshape((1,) + x.shape)
i = 0
for batch in training_data_generator.flow(x, batch_size=1, save_to_dir='previews',
    i += 1
    if i > 10:
        break
```

In [ ]:

```
training_data_dir=folder+'train/'
validation_data_dir=folder+'validation/'
test_data_dir=folder+'test/'
IMAGE_WIDTH=150
IMAGE_HEIGHT=150
BATCH_SIZE=20

training_generator = training_data_generator.flow_from_directory(
    training_data_dir,
    target_size=(IMAGE_WIDTH, IMAGE_HEIGHT),
    batch_size=BATCH_SIZE,
    class_mode='binary'
)
validation_generator = validation_data_generator.flow_from_directory(
    validation_data_dir,
    target_size=(IMAGE_WIDTH,IMAGE_HEIGHT),
    batch_size=BATCH_SIZE,
    class_mode='binary'
)
test_generator = test_data_generator.flow_from_directory(
    test_data_dir,
    target_size=(IMAGE_WIDTH,IMAGE_HEIGHT),
    batch_size=1,
    class_mode='binary',
    shuffle=False
)
```

```
Found 2000 images belonging to 2 classes.
Found 1000 images belonging to 2 classes.
Found 2000 images belonging to 2 classes.
```

In [ ]:

```
# Create a CNN classifier with at least 3 conv layers, 2 pooling layers, and two de

model = Sequential()
model.add(Conv2D(32, (3,3),activation='relu', input_shape=(IMAGE_HEIGHT,IMAGE_WIDTH
model.add(MaxPooling2D(pool_size=(3,3)))
```

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

model.add(Flatten())
model.add(Dense(100,activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(1,activation='sigmoid'))

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

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_4 (Conv2D)           (None, 148, 148, 32)      896

 max_pooling2d_4 (MaxPooling  (None, 49, 49, 32)       0
 2D)

 conv2d_5 (Conv2D)           (None, 47, 47, 32)        9248

 max_pooling2d_5 (MaxPooling  (None, 23, 23, 32)       0
 2D)

 flatten_2 (Flatten)         (None, 16928)             0


_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_4 (Conv2D)           (None, 148, 148, 32)      896

 max_pooling2d_4 (MaxPooling  (None, 49, 49, 32)       0
 2D)

 conv2d_5 (Conv2D)           (None, 47, 47, 32)        9248

 max_pooling2d_5 (MaxPooling  (None, 23, 23, 32)       0
 2D)

 flatten_2 (Flatten)         (None, 16928)             0

 dense_4 (Dense)             (None, 100)               1692900

 dropout_2 (Dropout)         (None, 100)               0

 dense_5 (Dense)             (None, 1)                 101

=================================================================
Total params: 1,703,145
Trainable params: 1,703,145
Non-trainable params: 0
_________________________________________________________________
```

In [ ]:

```
# Train the network on the training set, and report the performance of the classifi

EPOCHS=20
history = model.fit(
    training_generator,
    steps_per_epoch=len(training_generator.filenames) // BATCH_SIZE,
    epochs=EPOCHS,
    validation_data= validation_generator,
    validation_steps=len(validation_generator.filenames) // BATCH_SIZE)
```

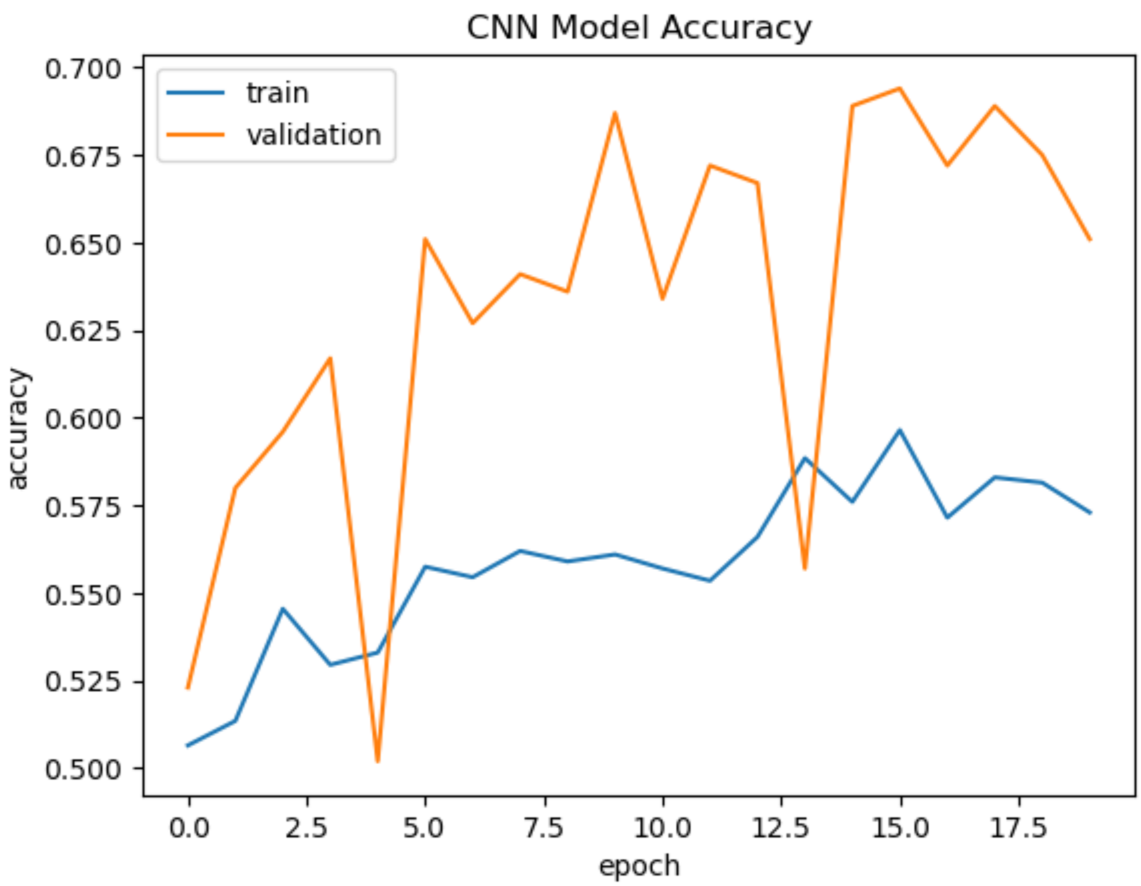
```
Epoch 1/20
100/100 [==============================] - 52s 506ms/step - loss: 0.7286 - accuracy:
0.5065 - val_loss: 0.6853 - val_accuracy: 0.5230
Epoch 2/20
100/100 [==============================] - 29s 286ms/step - loss: 0.7001 - accuracy:
0.5135 - val_loss: 0.6853 - val_accuracy: 0.5800
Epoch 3/20
100/100 [==============================] - 29s 288ms/step - loss: 0.7009 - accuracy:
0.5455 - val_loss: 0.6607 - val_accuracy: 0.5960
Epoch 4/20
100/100 [==============================] - 30s 300ms/step - loss: 0.6976 - accuracy:
0.5295 - val_loss: 0.6585 - val_accuracy: 0.6170
Epoch 5/20
100/100 [==============================] - 30s 295ms/step - loss: 0.6925 - accuracy:
0.5330 - val_loss: 0.8105 - val_accuracy: 0.5020
Epoch 6/20
100/100 [==============================] - 30s 296ms/step - loss: 0.6941 - accuracy:
0.5575 - val_loss: 0.6479 - val_accuracy: 0.6510
Epoch 7/20
100/100 [==============================] - 30s 297ms/step - loss: 0.6887 - accuracy:
0.5545 - val_loss: 0.6456 - val_accuracy: 0.6270
Epoch 8/20
100/100 [==============================] - 31s 309ms/step - loss: 0.6837 - accuracy:
0.5620 - val_loss: 0.6420 - val_accuracy: 0.6410
Epoch 9/20
100/100 [==============================] - 29s 290ms/step - loss: 0.6875 - accuracy:
0.5590 - val_loss: 0.6444 - val_accuracy: 0.6360
Epoch 10/20
100/100 [==============================] - 30s 299ms/step - loss: 0.6791 - accuracy:
0.5610 - val_loss: 0.6268 - val_accuracy: 0.6870
Epoch 11/20
100/100 [==============================] - 29s 292ms/step - loss: 0.6841 - accuracy:
0.5570 - val_loss: 0.6432 - val_accuracy: 0.6340
Epoch 12/20
100/100 [==============================] - 29s 288ms/step - loss: 0.6840 - accuracy:
0.5535 - val_loss: 0.6257 - val_accuracy: 0.6720
Epoch 13/20
100/100 [==============================] - 29s 290ms/step - loss: 0.6855 - accuracy:
0.5660 - val_loss: 0.6217 - val_accuracy: 0.6670
Epoch 14/20
100/100 [==============================] - 29s 293ms/step - loss: 0.6776 - accuracy:
0.5885 - val_loss: 0.7551 - val_accuracy: 0.5570
Epoch 15/20
100/100 [==============================] - 29s 292ms/step - loss: 0.6749 - accuracy:
0.5760 - val_loss: 0.6092 - val_accuracy: 0.6890
Epoch 16/20
100/100 [==============================] - 30s 298ms/step - loss: 0.6757 - accuracy:
0.5965 - val_loss: 0.6022 - val_accuracy: 0.6940
Epoch 17/20
100/100 [==============================] - 29s 290ms/step - loss: 0.6829 - accuracy:
0.5715 - val_loss: 0.6093 - val_accuracy: 0.6720
Epoch 18/20
100/100 [==============================] - 29s 287ms/step - loss: 0.6747 - accuracy:
0.5830 - val_loss: 0.5973 - val_accuracy: 0.6890
Epoch 19/20
100/100 [==============================] - 29s 292ms/step - loss: 0.6747 - accuracy:
```

```
0.5815 - val_loss: 0.6116 - val_accuracy: 0.6750
Epoch 20/20
100/100 [==============================] - 29s 292ms/step - loss: 0.6698 - accuracy:
0.5730 - val_loss: 0.6135 - val_accuracy: 0.6510
```

In [ ]:
```
_, acc = model.evaluate(test_generator, steps=len(test_generator), verbose=0)
print('Test Accuracy: %.3f%%' % (acc * 100.0))
```

```
Test Accuracy: 63.450%
```

In [ ]:
```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('CNN Model Accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```



In [ ]:
```
# Create a CNN classifier with at least 3 conv layers, 2 pooling layers, and two de

model = Sequential()
model.add(Conv2D(32, (3,3),activation='relu', input_shape=(IMAGE_HEIGHT,IMAGE_WIDTH
model.add(MaxPooling2D(pool_size=(3,3)))

model.add(Conv2D(32, (3,3),activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(rate=0.5))
model.add(BatchNormalization())
```

```
model.add(Flatten())
model.add(Dense(100,activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(1,activation='sigmoid'))

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

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_8 (Conv2D)           (None, 148, 148, 32)      896       
                                                                 
 max_pooling2d_8 (MaxPooling  (None, 49, 49, 32)       0         
 2D)                                                             
                                                                 
 conv2d_9 (Conv2D)           (None, 47, 47, 32)        9248      
                                                                 
 max_pooling2d_9 (MaxPooling  (None, 23, 23, 32)       0         
 2D)                                                             
                                                                 
```


```
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_8 (Conv2D)           (None, 148, 148, 32)      896       
                                                                 
 max_pooling2d_8 (MaxPooling  (None, 49, 49, 32)       0         
 2D)                                                             
                                                                 
 conv2d_9 (Conv2D)           (None, 47, 47, 32)        9248      
                                                                 
 max_pooling2d_9 (MaxPooling  (None, 23, 23, 32)       0         
 2D)                                                             
```


```
 dropout_4 (Dropout)         (None, 23, 23, 32)        0         
                                                                 
 batch_normalization (BatchN  (None, 23, 23, 32)       128       
 ormalization)                                                   
                                                                 
 flatten_3 (Flatten)         (None, 16928)             0         
                                                                 
 dense_6 (Dense)             (None, 100)               1692900   
                                                                 
 dropout_5 (Dropout)         (None, 100)               0         
                                                                 
 dense_7 (Dense)             (None, 1)                 101       
                                                                 
=================================================================
Total params: 1,703,273
Trainable params: 1,703,209
Non-trainable params: 64
_________________________________________________________________
```

In [ ]:

```
# Train the network on the training set, and report the performance of the classifi

EPOCHS=20
history = model.fit(
    training_generator,
    steps_per_epoch=len(training_generator.filenames) // BATCH_SIZE,
    epochs=EPOCHS,
    validation_data= validation_generator,
    validation_steps=len(validation_generator.filenames) // BATCH_SIZE)
```

```
Epoch 1/20
100/100 [==============================] - 31s 302ms/step - loss: 0.8511 - accuracy:
0.5165 - val_loss: 0.7393 - val_accuracy: 0.5000
Epoch 2/20
100/100 [==============================] - 30s 301ms/step - loss: 0.7098 - accuracy:
0.5165 - val_loss: 0.6823 - val_accuracy: 0.5460
Epoch 3/20
100/100 [==============================] - 29s 287ms/step - loss: 0.7118 - accuracy:
0.4990 - val_loss: 0.6931 - val_accuracy: 0.5060
Epoch 4/20
100/100 [==============================] - 31s 306ms/step - loss: 0.7596 - accuracy:
0.5100 - val_loss: 12.2248 - val_accuracy: 0.5120
Epoch 5/20
100/100 [==============================] - 33s 329ms/step - loss: 0.6928 - accuracy:
0.4980 - val_loss: 2.5046 - val_accuracy: 0.5160
Epoch 6/20
100/100 [==============================] - 29s 290ms/step - loss: 0.7419 - accuracy:
0.5315 - val_loss: 1.4176 - val_accuracy: 0.5040
Epoch 7/20
100/100 [==============================] - 29s 294ms/step - loss: 0.6996 - accuracy:
0.4905 - val_loss: 2.0283 - val_accuracy: 0.5010
Epoch 8/20
100/100 [==============================] - 30s 299ms/step - loss: 0.7749 - accuracy:
0.5200 - val_loss: 0.6806 - val_accuracy: 0.5720
Epoch 9/20
100/100 [==============================] - 32s 318ms/step - loss: 0.6976 - accuracy:
0.5125 - val_loss: 0.9279 - val_accuracy: 0.5010
Epoch 10/20
100/100 [==============================] - 31s 308ms/step - loss: 0.7007 - accuracy:
0.5200 - val_loss: 4.1070 - val_accuracy: 0.5160
Epoch 11/20
100/100 [==============================] - 30s 302ms/step - loss: 0.6965 - accuracy:
0.4995 - val_loss: 0.6725 - val_accuracy: 0.5940
Epoch 12/20
100/100 [==============================] - 30s 296ms/step - loss: 0.6935 - accuracy:
0.5165 - val_loss: 0.6840 - val_accuracy: 0.5490
Epoch 13/20
100/100 [==============================] - 30s 297ms/step - loss: 0.7356 - accuracy:
0.5080 - val_loss: 0.6866 - val_accuracy: 0.5130
Epoch 14/20
100/100 [==============================] - 31s 313ms/step - loss: 0.6904 - accuracy:
0.5245 - val_loss: 0.6901 - val_accuracy: 0.5920
Epoch 15/20
100/100 [==============================] - 30s 303ms/step - loss: 0.6932 - accuracy:
0.5255 - val_loss: 30.3642 - val_accuracy: 0.5030
Epoch 16/20
100/100 [==============================] - 31s 310ms/step - loss: 0.6983 - accuracy:
0.5250 - val_loss: 1.8637 - val_accuracy: 0.5210
Epoch 17/20
100/100 [==============================] - 31s 314ms/step - loss: 0.6977 - accuracy:
0.5175 - val_loss: 0.7000 - val_accuracy: 0.5010
Epoch 18/20
100/100 [==============================] - 30s 297ms/step - loss: 0.6948 - accuracy:
0.5265 - val_loss: 61.5443 - val_accuracy: 0.5030
Epoch 19/20
100/100 [==============================] - 31s 305ms/step - loss: 0.7385 - accuracy:
```

```
0.5295 - val_loss: 18.8697 - val_accuracy: 0.5530
Epoch 20/20
100/100 [==============================] - 32s 319ms/step - loss: 0.6961 - accuracy:
0.5415 - val_loss: 4.4147 - val_accuracy: 0.5030
```

In [ ]:
```python
_, acc = model.evaluate(test_generator, steps=len(test_generator), verbose=0)
print('Test Accuracy: %.3f%%' % (acc * 100.0))
```

```
Test Accuracy: 50.250%
```

In [ ]:
```python
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('CNN Model Accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```