

## Pet Classification Model Using CNN.

*# import libraries*

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.image import imread
import tensorflow
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Conv2D, MaxPool2D, Dropout,
BatchNormalization, Flatten
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.preprocessing.image import load_img,
ImageDataGenerator
import os
import random
from tabulate import tabulate
import warnings
warnings.filterwarnings('ignore')
```

*# !unzip data.zip*

*# show images (train dogs)*

```
plt.figure(figsize=(10, 5))
```

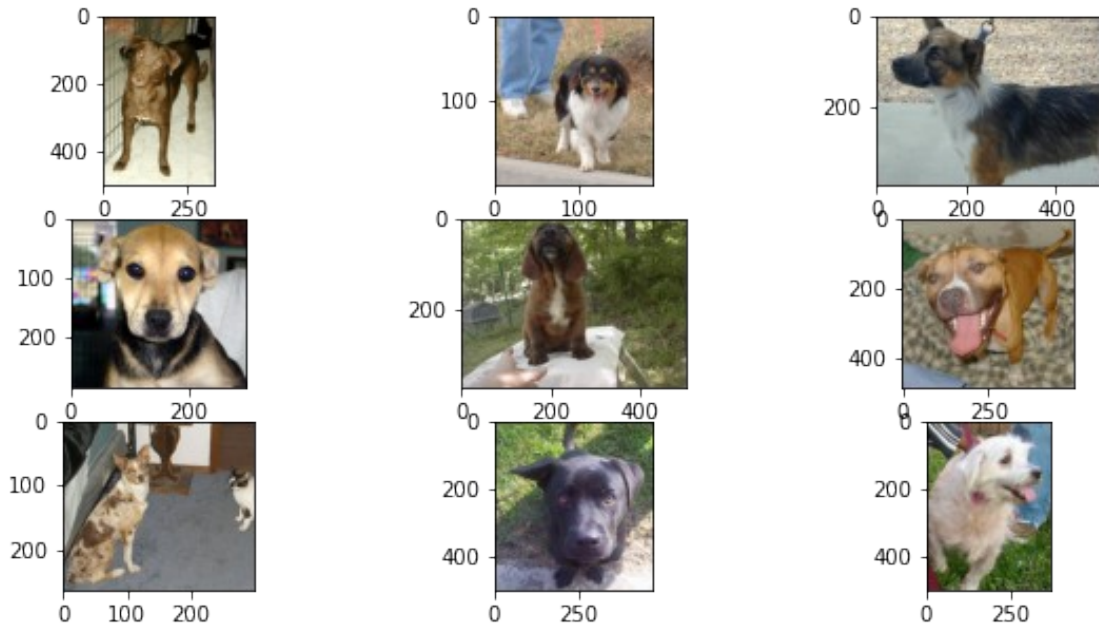
```
for i in range(9):
```

```
    j= i+1
```

```
    plt.subplot(3,3,j)
```

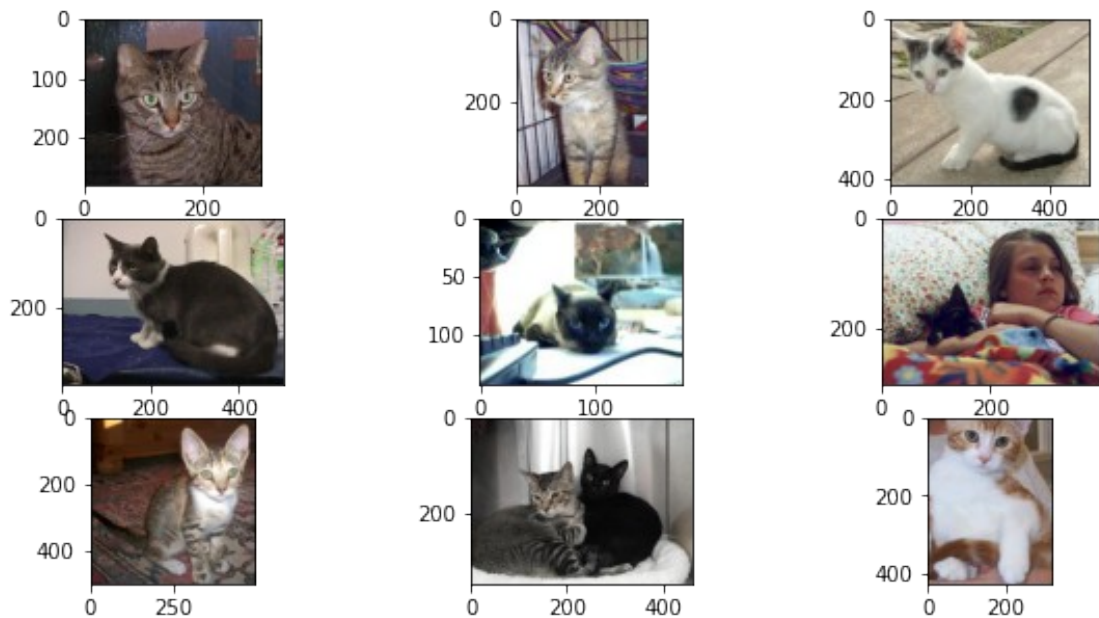
```
    img = imread('data/train/dogs/' + str(j) + '.jpg')
```

```
    plt.imshow(img)
```



```
# show images (train cats)
plt.figure(figsize=(10, 5))
for i in range(9):
    j= i+1
    plt.subplot(3,3,j)
    img = imread('data/train/cats/' + str(j) + '.jpg')

    plt.imshow(img)
```



```
# Prepare images for modelling
```

```
datagen2 = ImageDataGenerator(rescale = 1./255, shear_range =
0.2, zoom_range = 0.2,
                             validation_split = 0.2,
                             horizontal_flip = True,
                             featurewise_center=True,
                             featurewise_std_normalization=True,
                             rotation_range=90,
                             width_shift_range=0.1,
                             height_shift_range=0.1)
```

```
# trainset
```

```
training_set = datagen2.flow_from_directory('data/train',
classes=['dogs', 'cats'])
```

Found 40 images belonging to 2 classes.

```
validation_set = datagen2.flow_from_directory('data/test',
classes=['dogs', 'cats'])
```

Found 20 images belonging to 2 classes.

```
training_set.num_classes
```

```
2
```

```
training_set.image_shape
```

```
(256, 256, 3)
```

```
# list file names from cats and dogs folders in train
```

```
fn_cats = os.listdir('data/train/cats')
```

```
fn_dogs = os.listdir('data/train/dogs')
```

```
# categorize 0 for cats and 1 for dogs in train
```

```
categories = []
```

```
for image in fn_cats:
    category = image.split('.')[0]
    categories.append('cat')
```

```
for image in fn_dogs:
    category = image.split('.')[0]
    categories.append('dog')
```

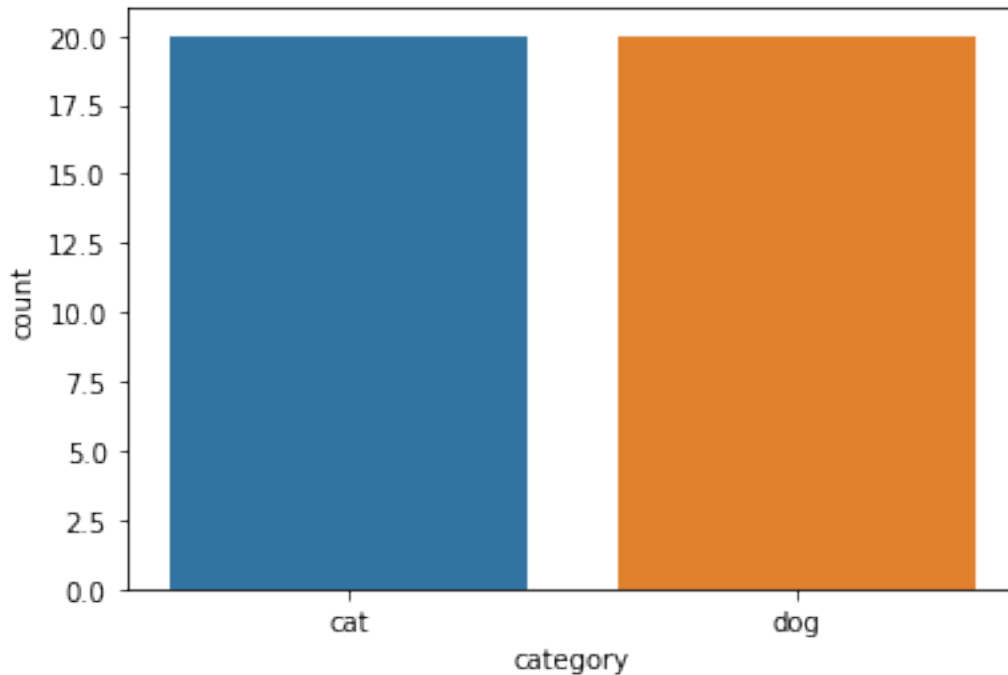
```
df = pd.DataFrame({'filename': fn_cats+fn_dogs,
                    'category': categories})
```

```
df.head()
```

```
   filename category
0    10.jpg       cat
1     1.jpg       cat
```

```
2  18.jpg      cat
3   9.jpg      cat
4  14.jpg      cat
```

```
sns.countplot(df['category'])
plt.show()
```



```
# list file names from cats and dogs folders in test
fn_test_cats = os.listdir('data/test/cats')
fn_test_dogs = os.listdir('data/test/dogs')

# categorize 0 for cats and 1 for dogs in train
categories = []

for image in fn_test_cats:
    category = image.split('.')[0]
    categories.append('cat')

for image in fn_test_dogs:
    category = image.split('.')[0]
    categories.append('dog')

df_test = pd.DataFrame({'filename': fn_test_cats+fn_test_dogs,
                        'category': categories})

df_test.head()

  filename category
0  108.jpg      cat
1  104.jpg      cat
```

```

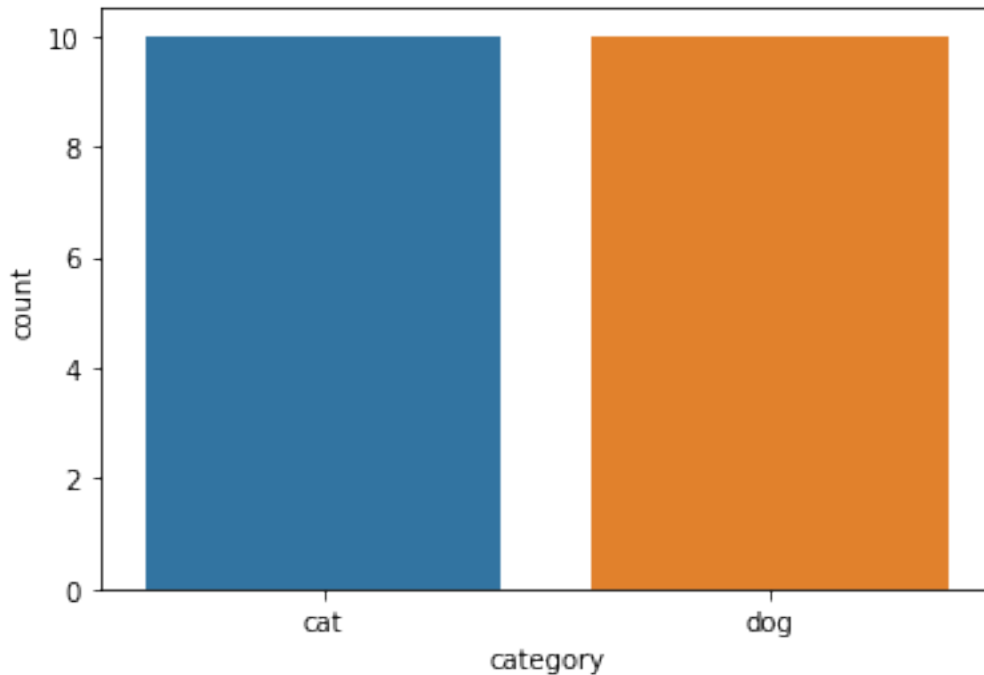
2  102.jpg      cat
3  106.jpg      cat
4  101.jpg      cat

```

```

sns.countplot(df_test['category'])
plt.show()

```



```

def createCNNModel():
    model = Sequential()
    model.add(Conv2D(name='conv_layer1', filters= 32, kernel_size=5,
                      activation='relu',
                      padding='valid',
                      input_shape=[256, 256, 3]))
    model.add(BatchNormalization())
    model.add(MaxPool2D(name='max_pool_layer1', pool_size= 2))
    model.add(Conv2D(name='conv_layer2', filters= 64, kernel_size=5,
                      activation='relu',
                      padding='valid'))
    model.add(BatchNormalization())
    model.add(MaxPool2D(name='max_pool_layer2', pool_size= 2))
    model.add(Flatten(name='flatten_layer'))
    model.add(Dense(units = 32, name='dense_layer1', activation =
'relu'))
    model.add(Dropout(0.4, name='dropout'))
    model.add(BatchNormalization())
    model.add(Dense(units= 2, name='dense_output', activation=
'softmax'))
    print(model.summary())
    return model

```

```

def compileAndTrainModel(model):
    model.compile(optimizer='adam',
                  loss = 'categorical_crossentropy',
                  metrics = ['accuracy'])
    return model

callback = EarlyStopping(monitor='val_loss', patience=5)

def fitAndEvaluateModel(model, epoch):
    history = model.fit(training_set,
                        validation_data = validation_set,
                        epochs=epoch,
                        callbacks=[callback])

    result = model.evaluate(validation_set)
    history = pd.DataFrame(history.history)
    return (history, model, result)

head = ['Loss', 'Accuracy']

data = []

history, model1, result =
fitAndEvaluateModel(compileAndTrainModel(createCNNModel()), 100)

```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv_layer1 (Conv2D)	(None, 252, 252, 32)	2432
batch_normalization (Batch Normalization)	(None, 252, 252, 32)	128
max_pool_layer1 (MaxPooling2D)	(None, 126, 126, 32)	0
conv_layer2 (Conv2D)	(None, 122, 122, 64)	51264
batch_normalization_1 (Batch Normalization)	(None, 122, 122, 64)	256
max_pool_layer2 (MaxPooling2D)	(None, 61, 61, 64)	0
flatten_layer (Flatten)	(None, 238144)	0
dense_layer1 (Dense)	(None, 32)	7620640
dropout (Dropout)	(None, 32)	0

batch_normalization_2 (Batch Normalization)	(None, 32)	128
dense_output (Dense)	(None, 2)	66

=====  
Total params: 7,674,914  
Trainable params: 7,674,658  
Non-trainable params: 256

---

None

Epoch 1/100

2/2 [=====] - 14s 7s/step - loss: 1.2341 - accuracy: 0.4750 - val\_loss: 1.0066 - val\_accuracy: 0.5000

Epoch 2/100

2/2 [=====] - 8s 2s/step - loss: 1.3852 - accuracy: 0.3500 - val\_loss: 1.1047 - val\_accuracy: 0.5500

Epoch 3/100

2/2 [=====] - 8s 2s/step - loss: 0.7700 - accuracy: 0.6000 - val\_loss: 0.8458 - val\_accuracy: 0.6000

Epoch 4/100

2/2 [=====] - 8s 6s/step - loss: 0.8164 - accuracy: 0.5250 - val\_loss: 0.8059 - val\_accuracy: 0.6000

Epoch 5/100

2/2 [=====] - 8s 6s/step - loss: 0.8944 - accuracy: 0.5750 - val\_loss: 0.7979 - val\_accuracy: 0.5000

Epoch 6/100

2/2 [=====] - 8s 2s/step - loss: 0.8699 - accuracy: 0.5250 - val\_loss: 0.7910 - val\_accuracy: 0.6500

Epoch 7/100

2/2 [=====] - 8s 2s/step - loss: 1.0607 - accuracy: 0.5000 - val\_loss: 0.8938 - val\_accuracy: 0.4500

Epoch 8/100

2/2 [=====] - 8s 2s/step - loss: 0.7861 - accuracy: 0.6000 - val\_loss: 0.8658 - val\_accuracy: 0.5000

Epoch 9/100

2/2 [=====] - 8s 2s/step - loss: 0.8331 - accuracy: 0.6750 - val\_loss: 0.7766 - val\_accuracy: 0.5000

Epoch 10/100

2/2 [=====] - 8s 6s/step - loss: 0.7952 - accuracy: 0.6500 - val\_loss: 0.8192 - val\_accuracy: 0.5000

Epoch 11/100

2/2 [=====] - 8s 6s/step - loss: 0.5107 - accuracy: 0.7500 - val\_loss: 0.7902 - val\_accuracy: 0.5500

Epoch 12/100

2/2 [=====] - 8s 6s/step - loss: 0.8072 - accuracy: 0.5750 - val\_loss: 0.7580 - val\_accuracy: 0.6000

Epoch 13/100

2/2 [=====] - 8s 2s/step - loss: 0.8608 - accuracy: 0.5250 - val\_loss: 0.8235 - val\_accuracy: 0.6000

```

Epoch 14/100
2/2 [=====] - 8s 6s/step - loss: 0.7424 -
accuracy: 0.7250 - val_loss: 0.8015 - val_accuracy: 0.5500
Epoch 15/100
2/2 [=====] - 8s 2s/step - loss: 0.8179 -
accuracy: 0.6500 - val_loss: 0.6113 - val_accuracy: 0.7000
Epoch 16/100
2/2 [=====] - 8s 2s/step - loss: 0.8000 -
accuracy: 0.5500 - val_loss: 0.7101 - val_accuracy: 0.5500
Epoch 17/100
2/2 [=====] - 8s 2s/step - loss: 0.8476 -
accuracy: 0.5500 - val_loss: 0.6368 - val_accuracy: 0.6500
Epoch 18/100
2/2 [=====] - 8s 6s/step - loss: 0.7052 -
accuracy: 0.7250 - val_loss: 0.7130 - val_accuracy: 0.6000
Epoch 19/100
2/2 [=====] - 8s 2s/step - loss: 0.5574 -
accuracy: 0.6750 - val_loss: 0.6977 - val_accuracy: 0.4500
Epoch 20/100
2/2 [=====] - 8s 2s/step - loss: 0.5802 -
accuracy: 0.7250 - val_loss: 0.7103 - val_accuracy: 0.5000
1/1 [=====] - 1s 1s/step - loss: 0.6969 -
accuracy: 0.6000

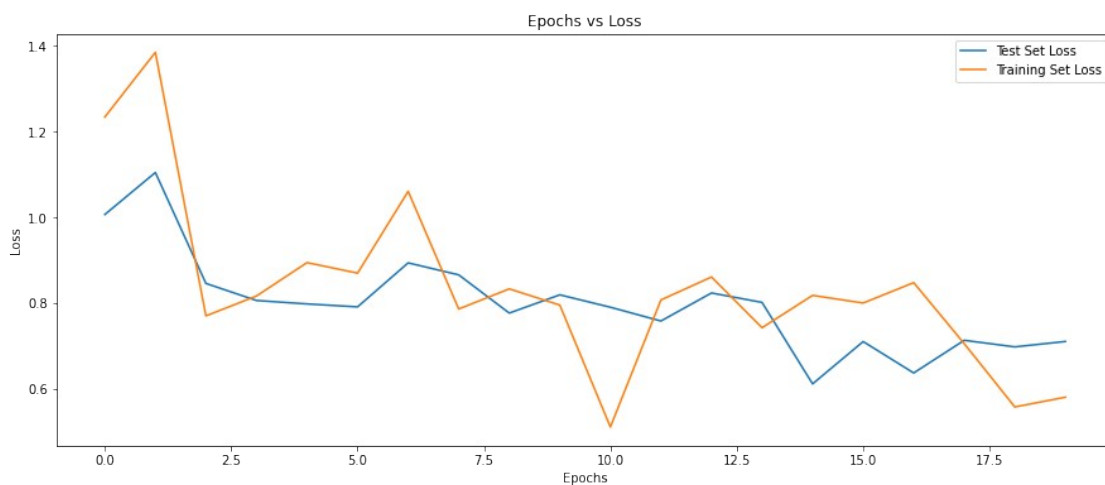
```

```
data.append(result)
```

```

plt.figure(figsize = (15,6))
plt.plot(history.iloc[:, 2], label='Test Set Loss')
plt.plot(history.iloc[:, 0], label='Training Set Loss')
plt.title('Epochs vs Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

```

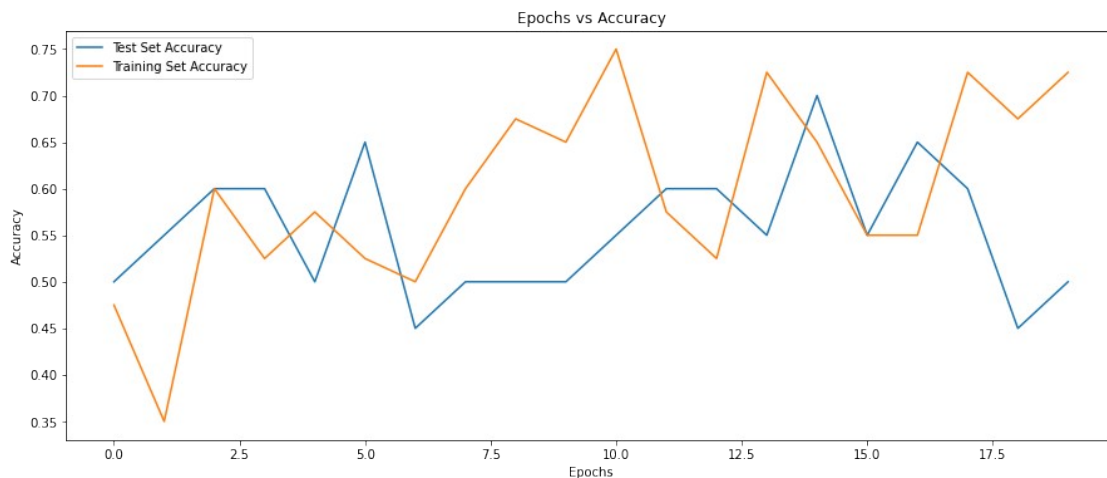




```

plt.figure(figsize = (15,6))
plt.plot(history.iloc[:, 3], label='Test Set Accuracy')
plt.plot(history.iloc[:, 1], label='Training Set Accuracy')
plt.title('Epochs vs Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

```



```

history, model2, result =
fitAndEvaluateModel(compileAndTrainModel(createCNNModel()), 200)

```

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
conv_layer1 (Conv2D)	(None, 252, 252, 32)	2432
batch_normalization_3 (Batch Normalization)	(None, 252, 252, 32)	128
max_pool_layer1 (MaxPooling2D)	(None, 126, 126, 32)	0
conv_layer2 (Conv2D)	(None, 122, 122, 64)	51264
batch_normalization_4 (Batch Normalization)	(None, 122, 122, 64)	256
max_pool_layer2 (MaxPooling2D)	(None, 61, 61, 64)	0
flatten_layer (Flatten)	(None, 238144)	0
dense_layer1 (Dense)	(None, 32)	7620640

dropout (Dropout)	(None, 32)	0
batch_normalization_5 (Batch Normalization)	(None, 32)	128
dense_output (Dense)	(None, 2)	66

```

=====
Total params: 7,674,914
Trainable params: 7,674,658
Non-trainable params: 256

```

```

None
Epoch 1/200
2/2 [=====] - 9s 3s/step - loss: 1.4617 - accuracy: 0.4250 - val_loss: 0.6787 - val_accuracy: 0.6000
Epoch 2/200
2/2 [=====] - 8s 6s/step - loss: 0.9153 - accuracy: 0.5750 - val_loss: 1.8401 - val_accuracy: 0.4000
Epoch 3/200
2/2 [=====] - 8s 2s/step - loss: 1.1229 - accuracy: 0.6000 - val_loss: 1.2681 - val_accuracy: 0.4500
Epoch 4/200
2/2 [=====] - 8s 2s/step - loss: 1.1271 - accuracy: 0.4750 - val_loss: 1.5638 - val_accuracy: 0.5000
Epoch 5/200
2/2 [=====] - 8s 2s/step - loss: 0.8852 - accuracy: 0.6750 - val_loss: 1.2136 - val_accuracy: 0.4500
Epoch 6/200
2/2 [=====] - 8s 2s/step - loss: 1.2147 - accuracy: 0.5750 - val_loss: 1.2022 - val_accuracy: 0.4000
1/1 [=====] - 1s 1s/step - loss: 1.1061 - accuracy: 0.4500

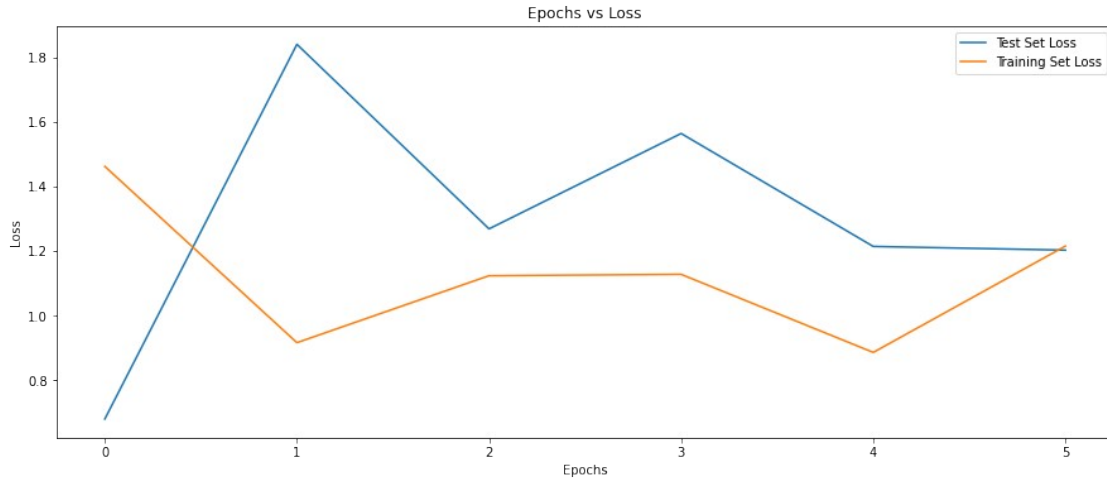
```

```
data.append(result)
```

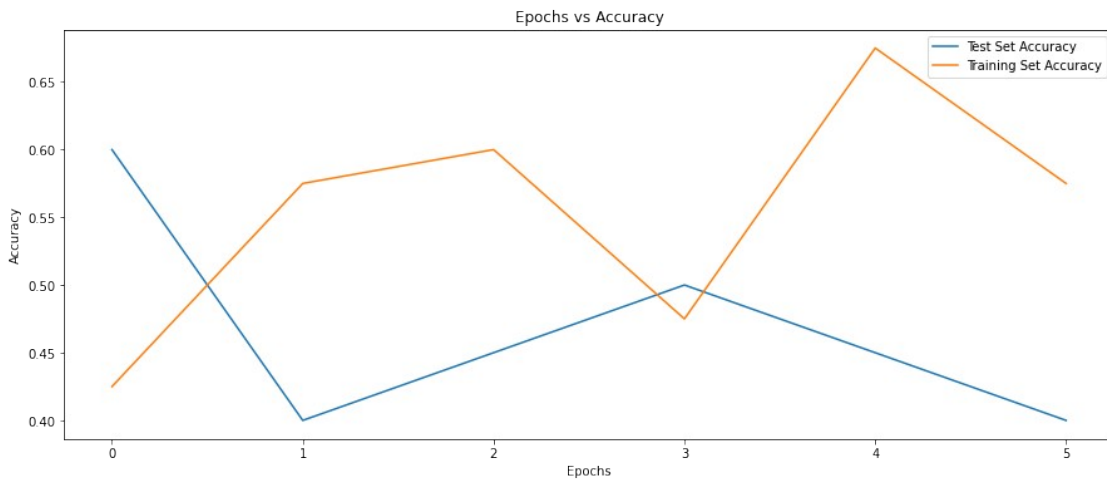
```

plt.figure(figsize = (15,6))
plt.plot(history.iloc[:, 2], label='Test Set Loss')
plt.plot(history.iloc[:, 0], label='Training Set Loss')
plt.title('Epochs vs Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

```



```
plt.figure(figsize = (15,6))
plt.plot(history.iloc[:, 3], label='Test Set Accuracy')
plt.plot(history.iloc[:, 1], label='Training Set Accuracy')
plt.title('Epochs vs Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



```
history, model3, result =
fitAndEvaluateModel(compileAndTrainModel(createCNNModel()), 300)
```

Model: "sequential\_2"

Layer (type)	Output Shape	Param #
conv_layer1 (Conv2D)	(None, 252, 252, 32)	2432
batch_normalization_6 (Batch Normalization)	(None, 252, 252, 32)	128

max_pool_layer1 (MaxPooling 2D)	(None, 126, 126, 32)	0
conv_layer2 (Conv2D)	(None, 122, 122, 64)	51264
batch_normalization_7 (Batch Normalization)	(None, 122, 122, 64)	256
max_pool_layer2 (MaxPooling 2D)	(None, 61, 61, 64)	0
flatten_layer (Flatten)	(None, 238144)	0
dense_layer1 (Dense)	(None, 32)	7620640
dropout (Dropout)	(None, 32)	0
batch_normalization_8 (Batch Normalization)	(None, 32)	128
dense_output (Dense)	(None, 2)	66

```

=====
Total params: 7,674,914
Trainable params: 7,674,658
Non-trainable params: 256

```

---

```

None
Epoch 1/300
2/2 [=====] - 9s 3s/step - loss: 1.2129 - accuracy: 0.4750 - val_loss: 4.5735 - val_accuracy: 0.5000
Epoch 2/300
2/2 [=====] - 8s 6s/step - loss: 1.1996 - accuracy: 0.5250 - val_loss: 2.8331 - val_accuracy: 0.5000
Epoch 3/300
2/2 [=====] - 8s 6s/step - loss: 0.8447 - accuracy: 0.6500 - val_loss: 2.4120 - val_accuracy: 0.5000
Epoch 4/300
2/2 [=====] - 8s 2s/step - loss: 1.3972 - accuracy: 0.5000 - val_loss: 2.0162 - val_accuracy: 0.4500
Epoch 5/300
2/2 [=====] - 8s 6s/step - loss: 1.3446 - accuracy: 0.3750 - val_loss: 1.8170 - val_accuracy: 0.3500
Epoch 6/300
2/2 [=====] - 8s 6s/step - loss: 1.0489 - accuracy: 0.5500 - val_loss: 1.4559 - val_accuracy: 0.5000
Epoch 7/300
2/2 [=====] - 8s 6s/step - loss: 0.9168 - accuracy: 0.5250 - val_loss: 1.0106 - val_accuracy: 0.4000
Epoch 8/300

```

2/2 [=====] - 8s 2s/step - loss: 0.9800 -  
accuracy: 0.5250 - val\_loss: 0.9949 - val\_accuracy: 0.4500  
Epoch 9/300  
2/2 [=====] - 8s 2s/step - loss: 0.9052 -  
accuracy: 0.6750 - val\_loss: 0.9003 - val\_accuracy: 0.3000  
Epoch 10/300  
2/2 [=====] - 8s 6s/step - loss: 0.7667 -  
accuracy: 0.6250 - val\_loss: 0.8555 - val\_accuracy: 0.5000  
Epoch 11/300  
2/2 [=====] - 8s 2s/step - loss: 0.7093 -  
accuracy: 0.6500 - val\_loss: 0.8422 - val\_accuracy: 0.4500  
Epoch 12/300  
2/2 [=====] - 8s 6s/step - loss: 0.8503 -  
accuracy: 0.5250 - val\_loss: 0.8236 - val\_accuracy: 0.5500  
Epoch 13/300  
2/2 [=====] - 8s 2s/step - loss: 1.0920 -  
accuracy: 0.5000 - val\_loss: 0.8879 - val\_accuracy: 0.5000  
Epoch 14/300  
2/2 [=====] - 8s 2s/step - loss: 0.9632 -  
accuracy: 0.6000 - val\_loss: 0.8132 - val\_accuracy: 0.5000  
Epoch 15/300  
2/2 [=====] - 8s 6s/step - loss: 0.8678 -  
accuracy: 0.5250 - val\_loss: 0.7725 - val\_accuracy: 0.5500  
Epoch 16/300  
2/2 [=====] - 8s 2s/step - loss: 0.7590 -  
accuracy: 0.6250 - val\_loss: 0.8080 - val\_accuracy: 0.5500  
Epoch 17/300  
2/2 [=====] - 8s 6s/step - loss: 0.5648 -  
accuracy: 0.6500 - val\_loss: 0.8351 - val\_accuracy: 0.4500  
Epoch 18/300  
2/2 [=====] - 8s 6s/step - loss: 0.8875 -  
accuracy: 0.5500 - val\_loss: 0.7647 - val\_accuracy: 0.6000  
Epoch 19/300  
2/2 [=====] - 8s 2s/step - loss: 0.9224 -  
accuracy: 0.5000 - val\_loss: 0.7545 - val\_accuracy: 0.6000  
Epoch 20/300  
2/2 [=====] - 8s 6s/step - loss: 0.8715 -  
accuracy: 0.5750 - val\_loss: 0.7705 - val\_accuracy: 0.5000  
Epoch 21/300  
2/2 [=====] - 8s 6s/step - loss: 0.6283 -  
accuracy: 0.6500 - val\_loss: 0.7873 - val\_accuracy: 0.5000  
Epoch 22/300  
2/2 [=====] - 8s 2s/step - loss: 0.6741 -  
accuracy: 0.5750 - val\_loss: 0.7706 - val\_accuracy: 0.5000  
Epoch 23/300  
2/2 [=====] - 8s 2s/step - loss: 0.6621 -  
accuracy: 0.6500 - val\_loss: 0.7756 - val\_accuracy: 0.5000  
Epoch 24/300  
2/2 [=====] - 8s 6s/step - loss: 0.5706 -  
accuracy: 0.7500 - val\_loss: 0.7527 - val\_accuracy: 0.5000

```

Epoch 25/300
2/2 [=====] - 8s 2s/step - loss: 0.6473 -
accuracy: 0.7250 - val_loss: 0.8159 - val_accuracy: 0.4000
Epoch 26/300
2/2 [=====] - 8s 2s/step - loss: 0.7852 -
accuracy: 0.6250 - val_loss: 0.8718 - val_accuracy: 0.3500
Epoch 27/300
2/2 [=====] - 8s 2s/step - loss: 0.5401 -
accuracy: 0.7250 - val_loss: 0.8070 - val_accuracy: 0.5000
Epoch 28/300
2/2 [=====] - 8s 6s/step - loss: 0.6477 -
accuracy: 0.6750 - val_loss: 0.8640 - val_accuracy: 0.4000
Epoch 29/300
2/2 [=====] - 8s 6s/step - loss: 0.6613 -
accuracy: 0.6500 - val_loss: 0.8502 - val_accuracy: 0.3500
1/1 [=====] - 1s 1s/step - loss: 0.7279 -
accuracy: 0.5500

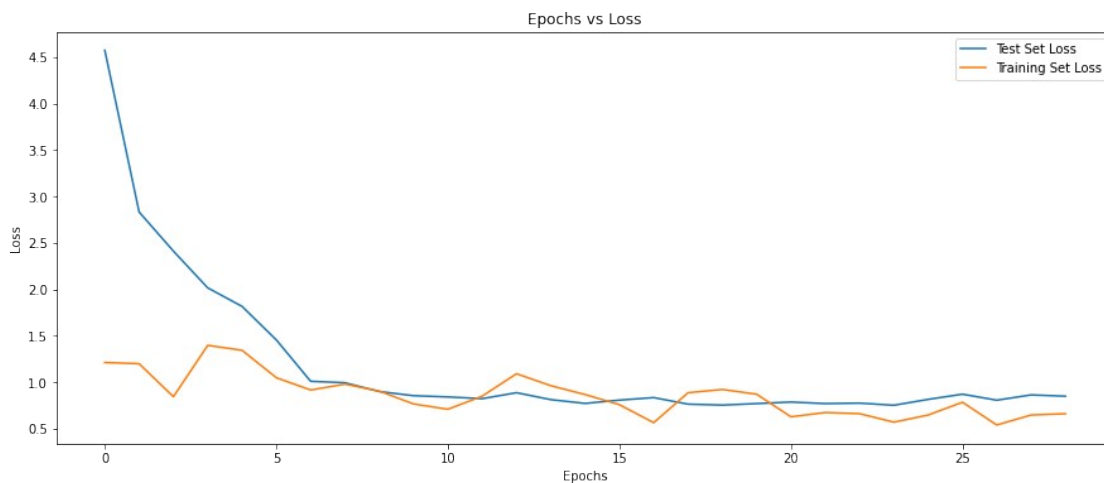
```

```
data.append(result)
```

```

plt.figure(figsize = (15,6))
plt.plot(history.iloc[:, 2], label='Test Set Loss')
plt.plot(history.iloc[:, 0], label='Training Set Loss')
plt.title('Epochs vs Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

```

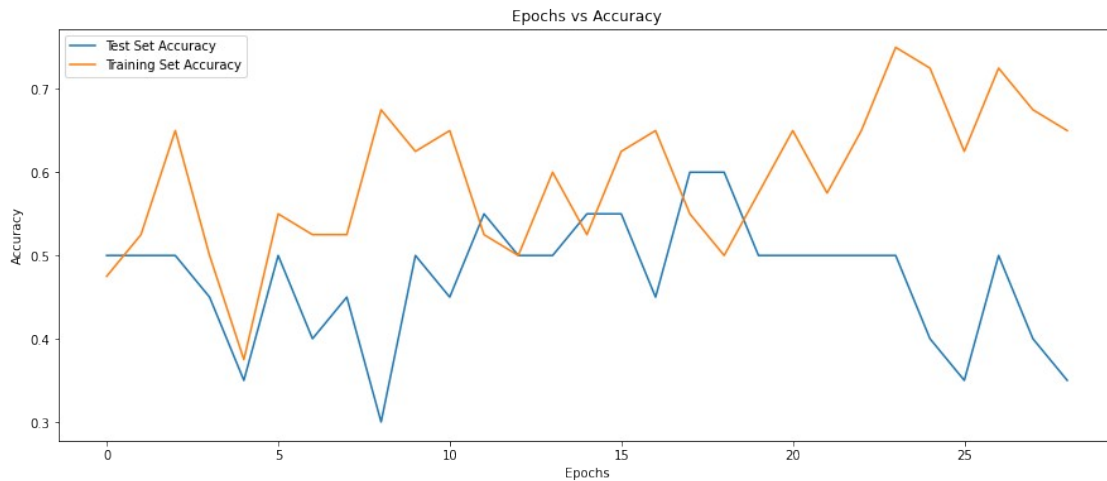


```

plt.figure(figsize = (15,6))
plt.plot(history.iloc[:, 3], label='Test Set Accuracy')
plt.plot(history.iloc[:, 1], label='Training Set Accuracy')
plt.title('Epochs vs Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')

```

```
plt.legend()
plt.show()
```



*# Report*

```
print(tabulate(data, headers=head, tablefmt="grid"))
```

```
+-----+-----+
|      Loss | Accuracy |
+=====+=====+
| 0.696867 |      0.6 |
+-----+-----+
| 1.10612  |      0.45|
+-----+-----+
| 0.727904 |      0.55|
+-----+-----+
```

Model 2 gave poor performance in terms of loss and accuracy. So we can go for model 1.

*# Predict the test images with optimal model*

```
pred = model1.predict(validation_set)
df_test['pred_category'] = np.argmax(pred, axis=1)
df_test['pred_category'] = df_test['pred_category'].replace({0:'cat',
1: 'dog'})
df_test.head(10)
```

```
filename category pred_category
0  108.jpg      cat          dog
1  104.jpg      cat          dog
2  102.jpg      cat          dog
3  106.jpg      cat          cat
4  101.jpg      cat          dog
5  110.jpg      cat          dog
6  109.jpg      cat          dog
7  105.jpg      cat          cat
```

8	103.jpg	cat	dog
9	107.jpg	cat	cat