```
In [1]: import tensorflow as tf
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
        from tensorflow.keras.optimizers import Adam, SGD
        from tensorflow.keras.preprocessing.image import ImageDataGenerator
        from tensorflow.keras.regularizers import 11 12
        from tensorflow.keras import models, layers
        import os
        from keras.models import load_model
In [2]:
        import tensorflow_datasets as tfds
         (ds_train, ds_test),ds_info=tfds.load('cats_vs_dogs',
                                               split=['train[:10%]', 'train[98%:]'],
                                               shuffle_files=True,
                                               as_supervised=True,
                                               with_info=True)
        image_size = (256, 256)
In [3]:
In [4]:
        #ds train=tf.keras.utils.image dataset from directory("ProjectDir Pet/train",batch
        #ds_test=tf.keras.utils.image_dataset_from_directory("ProjectDir_Pet/test",batch_st
In [5]:
        def normalize_img(image, label):
In [6]:
            # Resize the image to the desired dimensions
            image = tf.image.resize(image, image_size)
            # Normalize images: uint8 -> float32
            image = tf.cast(image, tf.float32) / 255.0
            return image, label
        ds_train = ds_train.map(normalize_img, num_parallel_calls=tf.data.AUTOTUNE)
        ds_train = ds_train.cache()
        ds_train = ds_train.shuffle(40)
        ds_train = ds_train.batch(128)
        ds_train = ds_train.prefetch(tf.data.AUTOTUNE)
In [7]: ds_test = ds_test.map(normalize_img, num_parallel_calls=tf.data.AUTOTUNE)
        ds_test = ds_test.batch(128)
        ds_test = ds_test.cache()
        ds_test = ds_test.prefetch(tf.data.AUTOTUNE)
In [8]: data_augmentation = tf.keras.Sequential([
          layers.RandomFlip("horizontal and vertical"),
          layers.RandomRotation(0.2),
        ])
In [9]:
        model = models.Sequential()
        model.add(layers.Input(shape=(256, 256, 3)))
        model.add(data_augmentation)
        model.add( layers.Conv2D( 32, (5, 5 ), activation = 'tanh',kernel_initializer='glo
        model.add(layers.BatchNormalization())
        model.add(layers.MaxPooling2D(2,2))
        model.add(layers.Conv2D(64, (5, 5), kernel initializer='glorot uniform', activation
        model.add(layers.BatchNormalization())
        model.add(layers.MaxPooling2D((2,2)))
        model.add(layers.Dropout(0.5))
        model.add(layers.Flatten())
        model.add(layers.Dense(32,kernel_initializer='he_normal',activation = 'relu'))
        model.add(layers.Dropout(0.5))
```

```
model.add(layers.BatchNormalization())
model.add(layers.Dense(1,kernel_initializer='he_normal', activation = 'sigmoid'))
```

In [10]: model.summary()

Model: "sequential 1"

Layer (type)	Output Shape	Param #
sequential (Sequential)	(None, 256, 256, 3)	0
conv2d (Conv2D)	(None, 252, 252, 32)	2432
<pre>batch_normalization (Batch Normalization)</pre>	(None, 252, 252, 32)	128
<pre>max_pooling2d (MaxPooling2 D)</pre>	(None, 126, 126, 32)	0
conv2d_1 (Conv2D)	(None, 122, 122, 64)	51264
<pre>batch_normalization_1 (Bat chNormalization)</pre>	(None, 122, 122, 64)	256
<pre>max_pooling2d_1 (MaxPoolin g2D)</pre>	(None, 61, 61, 64)	0
dropout (Dropout)	(None, 61, 61, 64)	0
flatten (Flatten)	(None, 238144)	0
dense (Dense)	(None, 32)	7620640
dropout_1 (Dropout)	(None, 32)	0
<pre>batch_normalization_2 (Bat chNormalization)</pre>	(None, 32)	128
dense_1 (Dense)	(None, 1)	33
<pre>rotal params: 7674881 (29.28 rainable params: 7674625 (2 on-trainable params: 256 (1 ristory = model.compile(optimizer = tf.keras.opt #loss='binary_crossentro #metrics=['accuracy'] loss = tf.keras.losses.B metrics=[tf.keras.metric</pre>	9.28 MB) .00 KB) cimizers.Adam(0.01), py', cinaryCrossentropy(from	om_logits= False),
history = model.fit(ds_train, epochs=50, validation_data=ds_test,) print('Number of total epoch len(history.history['val_bin	s ran:')	

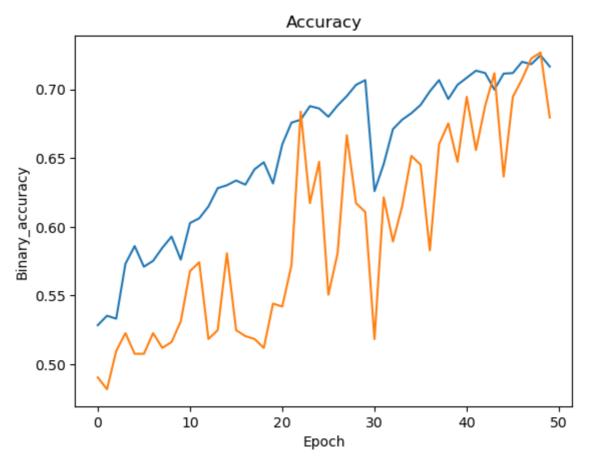
In [11]:

In [12]:

```
Epoch 1/50
uracy: 0.5284 - val_loss: 1.0589 - val_binary_accuracy: 0.4903
Epoch 2/50
uracy: 0.5353 - val_loss: 1.0581 - val_binary_accuracy: 0.4817
Epoch 3/50
uracy: 0.5331 - val_loss: 0.7093 - val_binary_accuracy: 0.5097
Epoch 4/50
uracy: 0.5731 - val_loss: 0.6974 - val_binary_accuracy: 0.5226
Epoch 5/50
uracy: 0.5860 - val_loss: 0.7032 - val_binary_accuracy: 0.5075
Epoch 6/50
uracy: 0.5709 - val_loss: 0.7270 - val_binary_accuracy: 0.5075
Epoch 7/50
uracy: 0.5752 - val_loss: 0.6963 - val_binary_accuracy: 0.5226
Epoch 8/50
uracy: 0.5847 - val_loss: 0.9562 - val_binary_accuracy: 0.5118
Epoch 9/50
uracy: 0.5929 - val_loss: 1.4730 - val_binary_accuracy: 0.5161
Epoch 10/50
uracy: 0.5761 - val_loss: 0.6976 - val_binary_accuracy: 0.5312
uracy: 0.6028 - val_loss: 0.6651 - val_binary_accuracy: 0.5677
Epoch 12/50
uracy: 0.6062 - val_loss: 0.6636 - val_binary_accuracy: 0.5742
Epoch 13/50
uracy: 0.6148 - val_loss: 0.7301 - val_binary_accuracy: 0.5183
Epoch 14/50
uracy: 0.6281 - val_loss: 0.7350 - val_binary_accuracy: 0.5247
Epoch 15/50
uracy: 0.6303 - val_loss: 0.6696 - val_binary_accuracy: 0.5806
Epoch 16/50
uracy: 0.6337 - val loss: 0.7402 - val binary accuracy: 0.5247
Epoch 17/50
uracy: 0.6307 - val_loss: 0.8598 - val_binary_accuracy: 0.5204
Epoch 18/50
uracy: 0.6419 - val_loss: 0.9740 - val_binary_accuracy: 0.5183
Epoch 19/50
uracy: 0.6470 - val_loss: 1.3085 - val_binary_accuracy: 0.5118
Epoch 20/50
uracy: 0.6316 - val_loss: 0.8805 - val_binary_accuracy: 0.5441
Epoch 21/50
uracy: 0.6599 - val_loss: 0.7905 - val_binary_accuracy: 0.5419
Epoch 22/50
```

```
uracy: 0.6758 - val_loss: 0.7130 - val_binary_accuracy: 0.5720
Epoch 23/50
uracy: 0.6780 - val loss: 0.6037 - val binary accuracy: 0.6839
Epoch 24/50
uracy: 0.6879 - val_loss: 0.6067 - val_binary_accuracy: 0.6172
Epoch 25/50
uracy: 0.6862 - val_loss: 0.5989 - val_binary_accuracy: 0.6473
Epoch 26/50
uracy: 0.6801 - val loss: 1.1014 - val binary accuracy: 0.5505
Epoch 27/50
uracy: 0.6883 - val_loss: 0.8039 - val_binary_accuracy: 0.5806
Epoch 28/50
uracy: 0.6952 - val_loss: 0.5916 - val_binary_accuracy: 0.6667
Epoch 29/50
uracy: 0.7034 - val_loss: 0.6450 - val_binary_accuracy: 0.6172
Epoch 30/50
uracy: 0.7068 - val_loss: 0.6807 - val_binary_accuracy: 0.6108
Epoch 31/50
uracy: 0.6260 - val_loss: 0.8155 - val_binary_accuracy: 0.5183
Epoch 32/50
uracy: 0.6457 - val_loss: 0.6681 - val_binary_accuracy: 0.6215
Epoch 33/50
uracy: 0.6711 - val_loss: 0.6843 - val_binary_accuracy: 0.5892
Epoch 34/50
uracy: 0.6780 - val_loss: 0.6479 - val_binary_accuracy: 0.6151
Epoch 35/50
uracy: 0.6827 - val_loss: 0.6256 - val_binary_accuracy: 0.6516
Epoch 36/50
uracy: 0.6887 - val_loss: 0.6168 - val_binary_accuracy: 0.6452
Epoch 37/50
uracy: 0.6986 - val_loss: 0.6980 - val_binary_accuracy: 0.5828
Epoch 38/50
uracy: 0.7068 - val_loss: 0.6146 - val_binary_accuracy: 0.6602
uracy: 0.6930 - val_loss: 0.5929 - val_binary_accuracy: 0.6753
Epoch 40/50
uracy: 0.7034 - val_loss: 0.6137 - val_binary_accuracy: 0.6473
Epoch 41/50
uracy: 0.7085 - val_loss: 0.5483 - val_binary_accuracy: 0.6946
uracy: 0.7137 - val_loss: 0.6239 - val_binary_accuracy: 0.6559
Epoch 43/50
19/19 [============== ] - 222s 12s/step - loss: 0.5488 - binary_acc
```

```
uracy: 0.7120 - val_loss: 0.5386 - val_binary_accuracy: 0.6882
      Epoch 44/50
      uracy: 0.6999 - val_loss: 0.5490 - val_binary_accuracy: 0.7118
      Epoch 45/50
      uracy: 0.7115 - val_loss: 0.6304 - val_binary_accuracy: 0.6366
      Epoch 46/50
      uracy: 0.7120 - val_loss: 0.5710 - val_binary_accuracy: 0.6946
      Epoch 47/50
      uracy: 0.7201 - val loss: 0.5689 - val binary accuracy: 0.7075
      Epoch 48/50
      uracy: 0.7184 - val_loss: 0.5359 - val_binary_accuracy: 0.7226
      Epoch 49/50
      19/19 [=============] - 227s 12s/step - loss: 0.5420 - binary_acc
      uracy: 0.7248 - val_loss: 0.5394 - val_binary_accuracy: 0.7269
      Epoch 50/50
      uracy: 0.7167 - val_loss: 0.5774 - val_binary_accuracy: 0.6796
      Number of total epochs ran:
Out[12]:
      #model.load_weights('best_model.h5')
In [13]:
In [14]:
      import matplotlib.pyplot as plt
      epochs= range(1, 50+1)
      plt.plot(history.history['binary_accuracy'])
      plt.plot(history.history['val_binary_accuracy'])
      plt.title('Accuracy')
      plt.ylabel('Binary_accuracy')
      plt.xlabel('Epoch')
      plt.show()
```



```
In [15]:
        import matplotlib.pyplot as plt
        class_name=['cat', 'dog']
        for images, labels in ds_test.take(20):
In [16]:
            predictions = model.predict(images)
        def image_print(i, prediction_arr, img):
            prediction_label = int(prediction_arr[i] >0.5) #1 if greater than 0.5, 0 if Les
            plt.imshow(img[i])
            plt.title(f'\n Predicted:{class_name[prediction_label]}')
            plt.axis('off')
        fig, axes = plt.subplots(4,5, figsize=(16,8))
        for i in range(20):#since there are 20 images
            plt.subplot(5,4, i+1)
            image_print(i, predictions, images)
        plt.show()
        4/4 [======== ] - 3s 601ms/step
        4/4 [======== ] - 2s 597ms/step
        4/4 [======== ] - 3s 642ms/step
        3/3 [======== ] - 2s 458ms/step
        C:\Users\selpa\AppData\Local\Temp\ipykernel_24768\2471148957.py:12: MatplotlibDepr
        ecationWarning: Auto-removal of overlapping axes is deprecated since 3.6 and will
        be removed two minor releases later; explicitly call ax.remove() as needed.
          plt.subplot(5,4, i+1)
```

Pet TFDS 9/12/23, 6:53 PM









Predicted:dog



Predicted:dog







Predicted:dog







Predicted:dog Predicted:cat



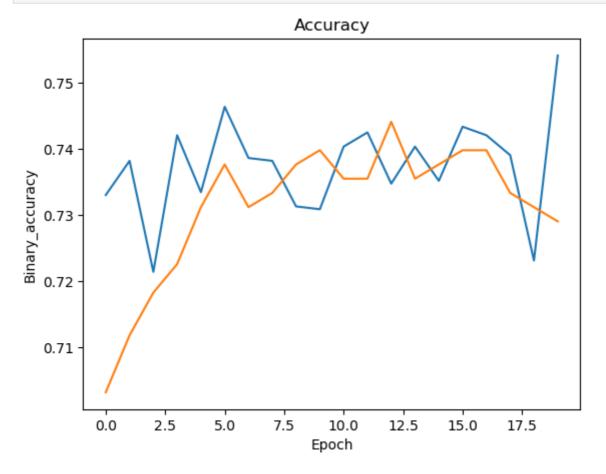


```
In [17]: history = model.compile(
             optimizer = tf.keras.optimizers.Adam(0.0001),
             #loss='binary_crossentropy',
             #metrics=['accuracy']
             loss = tf.keras.losses.BinaryCrossentropy(from_logits=False),
             metrics=[tf.keras.metrics.BinaryAccuracy()]
```

```
history = model.fit(
In [18]:
             ds_train,
             epochs=20,
             validation_data=ds_test,
         print('Number of total epochs ran:')
         len(history.history['val_binary_accuracy'])
```

```
Epoch 1/20
    uracy: 0.7330 - val_loss: 0.5507 - val_binary_accuracy: 0.7032
    Epoch 2/20
    uracy: 0.7382 - val_loss: 0.5366 - val_binary_accuracy: 0.7118
    Epoch 3/20
    uracy: 0.7214 - val_loss: 0.5259 - val_binary_accuracy: 0.7183
    Epoch 4/20
    uracy: 0.7420 - val_loss: 0.5189 - val_binary_accuracy: 0.7226
    Epoch 5/20
    uracy: 0.7334 - val_loss: 0.5140 - val_binary_accuracy: 0.7312
    Epoch 6/20
    uracy: 0.7463 - val_loss: 0.5115 - val_binary_accuracy: 0.7376
    Epoch 7/20
    uracy: 0.7386 - val_loss: 0.5098 - val_binary_accuracy: 0.7312
    Epoch 8/20
    uracy: 0.7382 - val_loss: 0.5083 - val_binary_accuracy: 0.7333
    Epoch 9/20
    uracy: 0.7313 - val_loss: 0.5076 - val_binary_accuracy: 0.7376
    Epoch 10/20
    uracy: 0.7309 - val_loss: 0.5073 - val_binary_accuracy: 0.7398
    uracy: 0.7403 - val_loss: 0.5070 - val_binary_accuracy: 0.7355
    Epoch 12/20
    uracy: 0.7425 - val_loss: 0.5072 - val_binary_accuracy: 0.7355
    Epoch 13/20
    uracy: 0.7347 - val_loss: 0.5075 - val_binary_accuracy: 0.7441
    Epoch 14/20
    uracy: 0.7403 - val_loss: 0.5070 - val_binary_accuracy: 0.7355
    Epoch 15/20
    uracy: 0.7352 - val_loss: 0.5067 - val_binary_accuracy: 0.7376
    Epoch 16/20
    uracy: 0.7433 - val loss: 0.5070 - val binary accuracy: 0.7398
    Epoch 17/20
    uracy: 0.7420 - val_loss: 0.5066 - val_binary_accuracy: 0.7398
    Epoch 18/20
    19/19 [==============] - 228s 12s/step - loss: 0.5175 - binary_acc
    uracy: 0.7390 - val_loss: 0.5069 - val_binary_accuracy: 0.7333
    Epoch 19/20
    uracy: 0.7231 - val_loss: 0.5074 - val_binary_accuracy: 0.7312
    Epoch 20/20
    uracy: 0.7541 - val loss: 0.5070 - val binary accuracy: 0.7290
    Number of total epochs ran:
Out[18]:
```

```
import matplotlib.pyplot as plt
epochs= range(1, 20+1)
plt.plot(history.history['binary_accuracy'])
plt.plot(history.history['val_binary_accuracy'])
plt.title('Accuracy')
plt.ylabel('Binary_accuracy')
plt.xlabel('Epoch')
plt.show()
```



```
Epoch 1/30
uracy: 0.7395 - val_loss: 0.5079 - val_binary_accuracy: 0.7462
Epoch 2/30
uracy: 0.7451 - val_loss: 0.5077 - val_binary_accuracy: 0.7398
Epoch 3/30
uracy: 0.7425 - val_loss: 0.5064 - val_binary_accuracy: 0.7290
Epoch 4/30
uracy: 0.7635 - val_loss: 0.5020 - val_binary_accuracy: 0.7398
Epoch 5/30
uracy: 0.7541 - val_loss: 0.5047 - val_binary_accuracy: 0.7398
Epoch 6/30
uracy: 0.7519 - val_loss: 0.5038 - val_binary_accuracy: 0.7226
Epoch 7/30
uracy: 0.7390 - val_loss: 0.5051 - val_binary_accuracy: 0.7269
Epoch 8/30
uracy: 0.7549 - val_loss: 0.5015 - val_binary_accuracy: 0.7398
Epoch 9/30
uracy: 0.7537 - val_loss: 0.4993 - val_binary_accuracy: 0.7548
Epoch 10/30
uracy: 0.7644 - val_loss: 0.5003 - val_binary_accuracy: 0.7462
uracy: 0.7489 - val_loss: 0.5008 - val_binary_accuracy: 0.7548
Epoch 12/30
uracy: 0.7489 - val_loss: 0.5089 - val_binary_accuracy: 0.7333
Epoch 13/30
uracy: 0.7494 - val_loss: 0.5075 - val_binary_accuracy: 0.7398
Epoch 14/30
uracy: 0.7657 - val_loss: 0.4990 - val_binary_accuracy: 0.7677
Epoch 15/30
uracy: 0.7567 - val_loss: 0.5008 - val_binary_accuracy: 0.7527
Epoch 16/30
uracy: 0.7545 - val loss: 0.4965 - val binary accuracy: 0.7527
Epoch 17/30
uracy: 0.7648 - val_loss: 0.4878 - val_binary_accuracy: 0.7699
Epoch 18/30
uracy: 0.7627 - val_loss: 0.4920 - val_binary_accuracy: 0.7484
Epoch 19/30
uracy: 0.7666 - val_loss: 0.4899 - val_binary_accuracy: 0.7570
Epoch 20/30
uracy: 0.7567 - val_loss: 0.4945 - val_binary_accuracy: 0.7505
Epoch 21/30
uracy: 0.7644 - val_loss: 0.4891 - val_binary_accuracy: 0.7441
Epoch 22/30
```

```
uracy: 0.7618 - val_loss: 0.4950 - val_binary_accuracy: 0.7398
     Epoch 23/30
     uracy: 0.7657 - val loss: 0.4995 - val binary accuracy: 0.7570
     Epoch 24/30
     uracy: 0.7567 - val_loss: 0.4960 - val_binary_accuracy: 0.7656
     Epoch 25/30
     uracy: 0.7631 - val_loss: 0.4968 - val_binary_accuracy: 0.7677
     Epoch 26/30
     uracy: 0.7739 - val loss: 0.4893 - val binary accuracy: 0.7656
     Epoch 27/30
     uracy: 0.7644 - val_loss: 0.4926 - val_binary_accuracy: 0.7441
     Epoch 28/30
     19/19 [=================== ] - 336s 18s/step - loss: 0.4662 - binary_acc
     uracy: 0.7730 - val_loss: 0.4895 - val_binary_accuracy: 0.7656
     Epoch 29/30
     uracy: 0.7653 - val_loss: 0.4848 - val_binary_accuracy: 0.7505
     Epoch 30/30
     uracy: 0.7657 - val_loss: 0.4851 - val_binary_accuracy: 0.7656
     Number of total epochs ran:
     30
Out[21]:
In [22]:
     import matplotlib.pyplot as plt
     epochs= range(1, 30+1)
     plt.plot(history.history['binary_accuracy'])
     plt.plot(history.history['val binary accuracy'])
     plt.title('Accuracy')
     plt.ylabel('Binary_accuracy')
     plt.xlabel('Epoch')
     plt.show()
```

