CAT AND DOG IMAGE CLASSIFIER

```
!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle/
```

```
!kaggle datasets download -d salader/dogs-vs-cats
```

```
Warning: Your Kaggle API key is readable by other users on this system! To fix this, you can run 'chmod 600 /root/.kaggle/kaggle.jso
dogs-vs-cats.zip: Skipping, found more recently modified local copy (use --force to force download)
```

```
import zipfile
zip_ref = zipfile.ZipFile('/content/dogs-vs-cats.zip', 'r')
zip_ref.extractall('/content')
zip_ref.close()
```

```
# Importing Dependencies
import tensorflow as tf
from tensorflow import keras
from keras import Sequential
from keras.layers import Dense, Conv2D, MaxPooling2D, Flatten
import matplotlib.pyplot as plt
```

```
# Keras generator
train_dataset = keras.utils.image_dataset_from_directory(
    directory = '/content/train',
    labels = 'inferred',
    label_mode = 'int',
    batch_size = 30,
    image_size = (256, 256)
)

validation_dataset = keras.utils.image_dataset_from_directory(
    directory = '/content/train',
    labels = 'inferred',
    label_mode = 'int',
    batch_size = 32,
    image_size = (256, 256)
)
```

```
Found 20000 files belonging to 2 classes.
Found 20000 files belonging to 2 classes.
```

```
# Normalizing
def process(image, label):
  image = tf.cast(image/255. , tf.float32)
  return image, label
train_dataset = train_dataset.map(process)
validation_dataset = validation_dataset.map(process)
```

```
# Creating CNN model
model = Sequential()
model.add(Conv2D(32, kernel_size = (3,3), padding = 'valid', activation = 'relu', input_shape = (256, 256, 3)))
model.add(MaxPooling2D(pool_size = (2,2), strides = 2, padding = 'valid'))
model.add(Conv2D(64, kernel_size = (3,3), padding = 'valid', activation = 'relu'))
model.add(MaxPooling2D(pool_size = (2,2), strides = 2, padding = 'valid'))
model.add(Conv2D(128, kernel_size = (3,3), padding = 'valid', activation = 'relu'))
model.add(MaxPooling2D(pool_size = (2,2), strides = 2, padding = 'valid'))
model.add(Flatten())
model.add(Dense(128, activation = 'relu'))
model.add(Dense(64, activation = 'relu'))
model.add(Dense(1, activation = 'sigmoid'))
```

```
model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_7 (Conv2D)           (None, 254, 254, 32)      896

 max_pooling2d_6 (MaxPoolin  (None, 127, 127, 32)      0
 g2D)

 conv2d_8 (Conv2D)           (None, 125, 125, 64)      18496
```

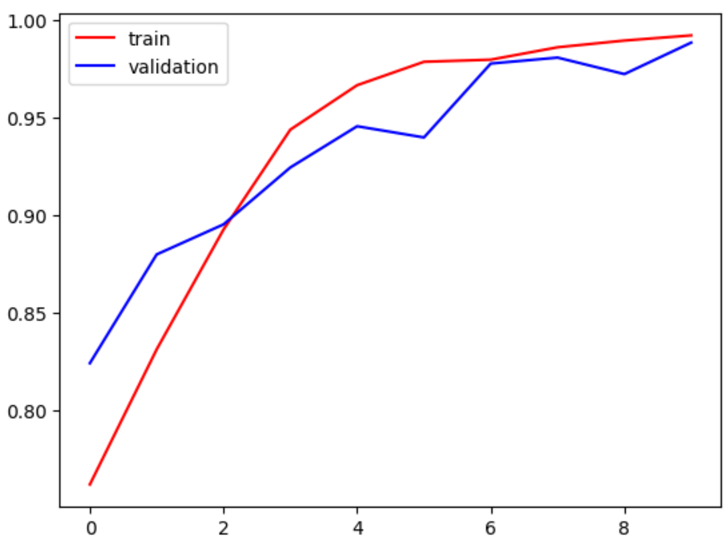
```
 max_pooling2d_7 (MaxPoolin  (None, 62, 62, 64)        0
 g2D)

 conv2d_9 (Conv2D)           (None, 60, 60, 128)       73856

 max_pooling2d_8 (MaxPoolin  (None, 30, 30, 128)       0
 g2D)

 flatten_2 (Flatten)         (None, 115200)            0

 dense_6 (Dense)             (None, 128)               14745728

 dense_7 (Dense)             (None, 64)                8256

 dense_8 (Dense)             (None, 1)                 65

=================================================================
Total params: 14847297 (56.64 MB)
Trainable params: 14847297 (56.64 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
# Compiling Model
model.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
```

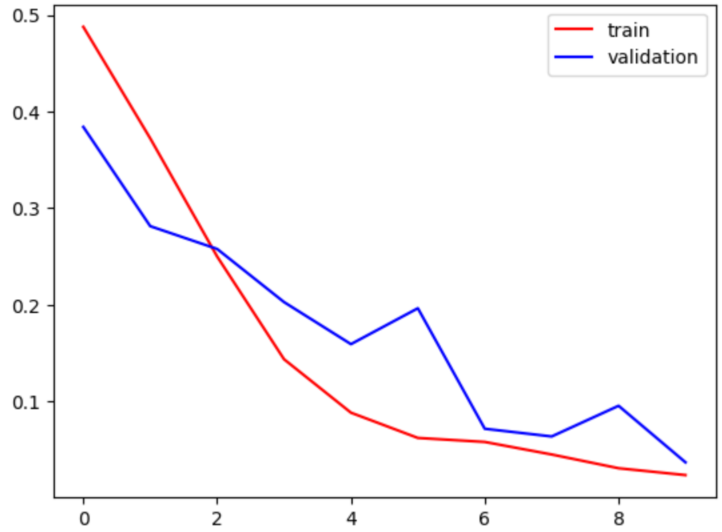
```
history = model.fit(train_dataset, epochs = 10, validation_data = validation_dataset)
```

```
Epoch 1/10
667/667 [==============================] - 74s 108ms/step - loss: 0.4878 - accuracy: 0.7618 - val_loss: 0.3841 - val_accuracy: 0.824
Epoch 2/10
667/667 [==============================] - 83s 125ms/step - loss: 0.3722 - accuracy: 0.8311 - val_loss: 0.2813 - val_accuracy: 0.879
Epoch 3/10
667/667 [==============================] - 83s 124ms/step - loss: 0.2498 - accuracy: 0.8926 - val_loss: 0.2577 - val_accuracy: 0.895
Epoch 4/10
667/667 [==============================] - 84s 125ms/step - loss: 0.1434 - accuracy: 0.9438 - val_loss: 0.2026 - val_accuracy: 0.924
Epoch 5/10
667/667 [==============================] - 83s 124ms/step - loss: 0.0881 - accuracy: 0.9667 - val_loss: 0.1591 - val_accuracy: 0.945
Epoch 6/10
667/667 [==============================] - 83s 124ms/step - loss: 0.0619 - accuracy: 0.9786 - val_loss: 0.1962 - val_accuracy: 0.939
Epoch 7/10
667/667 [==============================] - 84s 125ms/step - loss: 0.0577 - accuracy: 0.9797 - val_loss: 0.0714 - val_accuracy: 0.977
Epoch 8/10
667/667 [==============================] - 71s 106ms/step - loss: 0.0447 - accuracy: 0.9861 - val_loss: 0.0634 - val_accuracy: 0.980
Epoch 9/10
667/667 [==============================] - 83s 124ms/step - loss: 0.0305 - accuracy: 0.9895 - val_loss: 0.0952 - val_accuracy: 0.972
Epoch 10/10
667/667 [==============================] - 83s 124ms/step - loss: 0.0234 - accuracy: 0.9922 - val_loss: 0.0366 - val_accuracy: 0.988
```

```
# Getting graph of our model
plt.plot(history.history['accuracy'], color = 'red', label = 'train')
plt.plot(history.history['val_accuracy'], color = 'blue', label = 'validation')
plt.legend()
plt.show()
```




```
plt.plot(history.history['loss'], color = 'red', label = 'train')
plt.plot(history.history['val_loss'], color = 'blue', label = 'validation')
plt.legend()
plt.show()
```



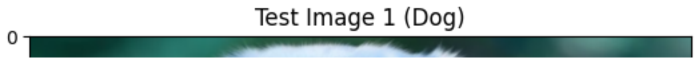
OBSERVATION

- The validation accuracy is increasing as the number of epochs increases, which means that the model is learning and improving. However, it is still lower than the training accuracy, which means that the model is still overfitting to the training data.
- The final validation accuracy achieved after 10 epochs is approximately 98.47%. This indicates that the model is able to correctly classify around 98.85% of the samples in the validation dataset.

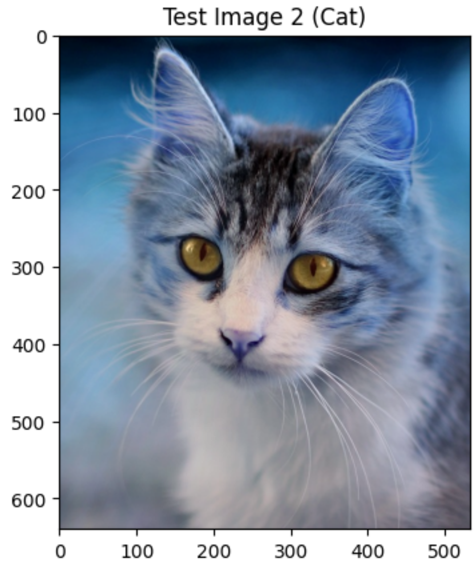
```
# Saving the model
model_path = '/content/cat_dog_classifier_model'
model.save(model_path)
print("Model saved successfully.")
```

```
Model saved successfully.
```

```
import cv2
import matplotlib.pyplot as plt

# Load the test images
test_img1 = cv2.imread('/content/dogg.jpg')
cat_image = cv2.imread('/content/cat.jpg')

plt.imshow(test_img1)
plt.title("Test Image 1 (Dog)")
plt.show()

test_img1 = cv2.resize(test_img1, (256, 256))
test_img1 = test_img1.astype(float) / 255.0
input_image1 = test_img1.reshape((1, 256, 256, 3))

prediction1 = model.predict(input_image1)

threshold = 0.5
if prediction1 >= threshold:
    print("Test Image 1 (Dog) Prediction: Dog")
else:
    print("Test Image 1 (Dog) Prediction: Cat")
```




```
plt.imshow(cat_image)
plt.title("Test Image 2 (Cat)")
plt.show()

cat_image = cv2.resize(cat_image, (256, 256))
cat_image = cat_image.astype(float) / 255.0
input_image2 = cat_image.reshape((1, 256, 256, 3))

prediction2 = model.predict(input_image2)

if prediction2 >= threshold:
    print("Test Image 2 (Cat) Prediction: Dog")
else:
    print("Test Image 2 (Cat) Prediction: Cat")
```




```
1/1 [==============================] - 0s 56ms/step
Test Image 2 (Cat) Prediction: Cat
```

OBSERVATION

- The model performs well in classifying cat and dog images, achieving a high accuracy of around 98.85% on the validation set.
- However, some overfitting is observed, indicating the need for regularization techniques like dropout or data augmentation to improve generalization.
- The trained model is saved for future use.
- Predictions on new images (one cat and one dog image) are made using the trained model, demonstrating its applicability.