

```
1 import tensorflow as tf
2 from tensorflow.keras.models import Sequential
3 from tensorflow.keras.layers import Dense, Conv2D, Flatten, Dropout, MaxPooling2D
4 from tensorflow.keras.preprocessing.image import ImageDataGenerator
5
6 import os
7 import numpy as np
8 import matplotlib.pyplot as plt
```

```
1 from google.colab import files
2 files.upload()
3 ! rm -rf ~/.kaggle/
4 ! mkdir ~/.kaggle
5 ! cp kaggle.json ~/.kaggle/
6 ! chmod 600 ~/.kaggle/kaggle.json
```



Choose Files kaggle.json

- **kaggle.json**(application/json) - 62 bytes, last modified: 4/3/2020 - 100% done
- Saving kaggle.json to kaggle (1).json

```
1 ! pip install -q kaggle
```

```
1 !pip uninstall -y kaggle
2 !pip install --upgrade pip
3 !pip install kaggle==1.5.6
4 !kaggle -v
```



```

Uninstalling kaggle-1.5.6:
  Successfully uninstalled kaggle-1.5.6
Collecting pip
  Downloading https://files.pythonhosted.org/packages/54/0c/d01aa759fdc501a58f431eb594a1
|████████████████████| 1.4MB 2.8MB/s
Installing collected packages: pip
  Found existing installation: pip 19.3.1
  Uninstalling pip-19.3.1:
    Successfully uninstalled pip-19.3.1
  Successfully installed pip-20.0.2
Collecting kaggle==1.5.6
  Downloading kaggle-1.5.6.tar.gz (58 kB)
|████████████████████| 58 kB 1.8 MB/s
Requirement already satisfied: urllib3<1.25,>=1.21.1 in /usr/local/lib/python3.6/dist-packages (from kaggle)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.6/dist-packages (from kaggle)
Requirement already satisfied: certifi in /usr/local/lib/python3.6/dist-packages (from kaggle)
Requirement already satisfied: python-dateutil in /usr/local/lib/python3.6/dist-packages (from kaggle)
Requirement already satisfied: requests in /usr/local/lib/python3.6/dist-packages (from kaggle)
Requirement already satisfied: tqdm in /usr/local/lib/python3.6/dist-packages (from kaggle)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.6/dist-packages (from kaggle)
Requirement already satisfied: idna<2.9,>=2.5 in /usr/local/lib/python3.6/dist-packages (from kaggle)
Requirement already satisfied: chardet<3.1.0,>=3.0.2 in /usr/local/lib/python3.6/dist-packages (from kaggle)
Requirement already satisfied: text-unidecode>=1.3 in /usr/local/lib/python3.6/dist-packages (from kaggle)
Building wheels for collected packages: kaggle
  Building wheel for kaggle (setup.py) ... done
  Created wheel for kaggle: filename=kaggle-1.5.6-py3-none-any.whl size=72859 sha256=b2e
  Stored in directory: /root/.cache/pip/wheels/01/3e/ff/77407ebac3ef71a79b9166a8382aecf8
Successfully built kaggle
Installing collected packages: kaggle
Successfully installed kaggle-1.5.6
Kaggle API 1.5.6

```

```
1 ! kaggle competitions download -c dogs-vs-cats
```

```

↳ Downloading dogs-vs-cats.zip to /content
100% 809M/812M [00:16<00:00, 72.3MB/s]
100% 812M/812M [00:16<00:00, 52.9MB/s]

```

```

1 ! mkdir dogs-vs-cats
2 ! unzip dogs-vs-cats -d dogs-vs-cats

```

```

↳ Archive: dogs-vs-cats.zip
  inflating: dogs-vs-cats/sampleSubmission.csv
  inflating: dogs-vs-cats/test1.zip
  inflating: dogs-vs-cats/train.zip

```

```

1 ! mkdir train
2 ! unzip dogs-vs-cats/train -d train
3 ! mkdir test
4 ! unzip dogs-vs-cats/test1 -d test

```

```
1 ! mkdir train/train/dog/
```

```

2  ! mkdir train/train/cat/

1  !mv train/train/cat.* train/train/cat
2  !mv train/train/dog.* train/train/dog

1  !mkdir validation/
2  !mkdir validation/cat/
3  !mkdir validation/dog/
4  !mv train/train/cat/cat.1?????.jpg validation/cat/
5  !mv train/train/dog/dog.1?????.jpg validation/dog/

1  train_dir = 'train/train/'
2  validation_dir = 'validation'
3  train_cats_dir = 'train/train/cat/'
4  train_dogs_dir = 'train/train/dog/'
5  validation_cats_dir = 'validation/cat/'
6  validation_dogs_dir = 'validation/dog/'
7
8  num_cats_tr = len(os.listdir(train_cats_dir))
9  num_dogs_tr = len(os.listdir(train_dogs_dir))
10
11 num_cats_val = len(os.listdir(validation_cats_dir))
12 num_dogs_val = len(os.listdir(validation_dogs_dir))
13
14 total_train = num_cats_tr + num_dogs_tr
15 total_val = num_cats_val + num_dogs_val

```

Задание 1. Загрузите данные. Разделите исходный набор данных на обучающую, валидационную

```

1  print('total training cat images:', num_cats_tr)
2  print('total training dog images:', num_dogs_tr)
3
4  print('total validation cat images:', num_cats_val)
5  print('total validation dog images:', num_dogs_val)
6  print("--")
7  print("Total training images:", total_train)
8  print("Total validation images:", total_val)

```

```

📄 total training cat images: 10000
total training dog images: 10000
total validation cat images: 2500
total validation dog images: 2500
--
Total training images: 20000
Total validation images: 5000

```

```

1  batch_size = 128
2  epochs = 15
3  IMG_HEIGHT = 150
4  IMG_WIDTH = 150

```

```
4 IMG_WIDTH = 150
```

```
1 train_image_generator = ImageDataGenerator(rescale=1./255)
2 validation_image_generator = ImageDataGenerator(rescale=1./255)
```

```
1 train_data_gen = train_image_generator.flow_from_directory(batch_size=batch_size,
2                                                             directory=train_dir,
3                                                             shuffle=True,
4                                                             target_size=(IMG_HEIGHT, IMG_
5                                                             class_mode='binary')
```

↳ Found 20000 images belonging to 2 classes.

```
1 val_data_gen = validation_image_generator.flow_from_directory(batch_size=batch_size,
2                                                                directory=validation_dir,
3                                                                target_size=(IMG_HEIGHT, I
4                                                                class_mode='binary')
```

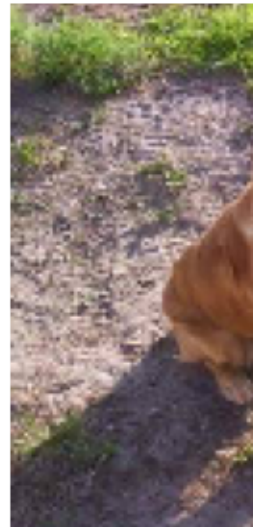
↳ Found 5000 images belonging to 2 classes.

```
1 sample_training_images, _ = next(train_data_gen)
```

```
1 def plotImages(images_arr):
2     fig, axes = plt.subplots(1, 5, figsize=(20,20))
3     axes = axes.flatten()
4     for img, ax in zip( images_arr, axes):
5         ax.imshow(img)
6         ax.axis('off')
7     plt.tight_layout()
8     plt.show()
```

```
1 plotImages(sample_training_images[:5])
```

↳



Задание 2. Реализуйте глубокую нейронную сеть с как минимум тремя сверточными слоями. |
получено?

```
1 model = Sequential([
2     Conv2D(16, 3, padding='same', activation='relu', input_shape=(IMG_HEIGHT, IMG_WIDTH
3     MaxPooling2D(),
4     Conv2D(32, 3, padding='same', activation='relu'),
5     MaxPooling2D(),
6     Conv2D(64, 3, padding='same', activation='relu'),
7     MaxPooling2D(),
8     Flatten(),
9     Dense(512, activation='relu'),
10    Dense(1)
11 ])
12 model.compile(optimizer='adam',
13               loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
14               metrics=['accuracy'])
15 model.summary()
```

📄 Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 150, 150, 16)	448
max_pooling2d (MaxPooling2D)	(None, 75, 75, 16)	0
conv2d_1 (Conv2D)	(None, 75, 75, 32)	4640
max_pooling2d_1 (MaxPooling2D)	(None, 37, 37, 32)	0
conv2d_2 (Conv2D)	(None, 37, 37, 64)	18496
max_pooling2d_2 (MaxPooling2D)	(None, 18, 18, 64)	0
flatten (Flatten)	(None, 20736)	0
dense (Dense)	(None, 512)	10617344
dense_1 (Dense)	(None, 1)	513
Total params: 10,641,441		
Trainable params: 10,641,441		
Non-trainable params: 0		

```
1 history = model.fit_generator(
2     train_data_gen,
3     steps_per_epoch=total_train // batch_size,
4     epochs=epochs,
5     validation_data=val_data_gen,
6     validation_steps=total_val // batch_size
```

```
validation_steps = total_val // batch_size
7 )
```

⚠ WARNING:tensorflow:From <ipython-input-23-01c6f78f4d4f>:6: Model.fit_generator (from ten Instructions for updating:
Please use Model.fit, which supports generators.

Epoch 1/15

156/156 [=====] - 68s 433ms/step - loss: 0.6665 - accuracy: 0.6

Epoch 2/15

156/156 [=====] - 65s 420ms/step - loss: 0.5068 - accuracy: 0.7

Epoch 3/15

156/156 [=====] - 69s 440ms/step - loss: 0.4463 - accuracy: 0.7

Epoch 4/15

156/156 [=====] - 66s 424ms/step - loss: 0.3983 - accuracy: 0.8

Epoch 5/15

156/156 [=====] - 65s 419ms/step - loss: 0.3430 - accuracy: 0.8

Epoch 6/15

156/156 [=====] - 65s 417ms/step - loss: 0.3068 - accuracy: 0.8

Epoch 7/15

156/156 [=====] - 66s 423ms/step - loss: 0.2346 - accuracy: 0.8

Epoch 8/15

156/156 [=====] - 66s 420ms/step - loss: 0.1781 - accuracy: 0.9

Epoch 9/15

156/156 [=====] - 66s 421ms/step - loss: 0.1221 - accuracy: 0.9

Epoch 10/15

156/156 [=====] - 66s 421ms/step - loss: 0.0740 - accuracy: 0.9

Epoch 11/15

156/156 [=====] - 65s 416ms/step - loss: 0.0503 - accuracy: 0.9

Epoch 12/15

156/156 [=====] - 65s 419ms/step - loss: 0.0293 - accuracy: 0.9

Epoch 13/15

156/156 [=====] - 65s 414ms/step - loss: 0.0304 - accuracy: 0.9

Epoch 14/15

156/156 [=====] - 64s 413ms/step - loss: 0.0161 - accuracy: 0.9

Epoch 15/15

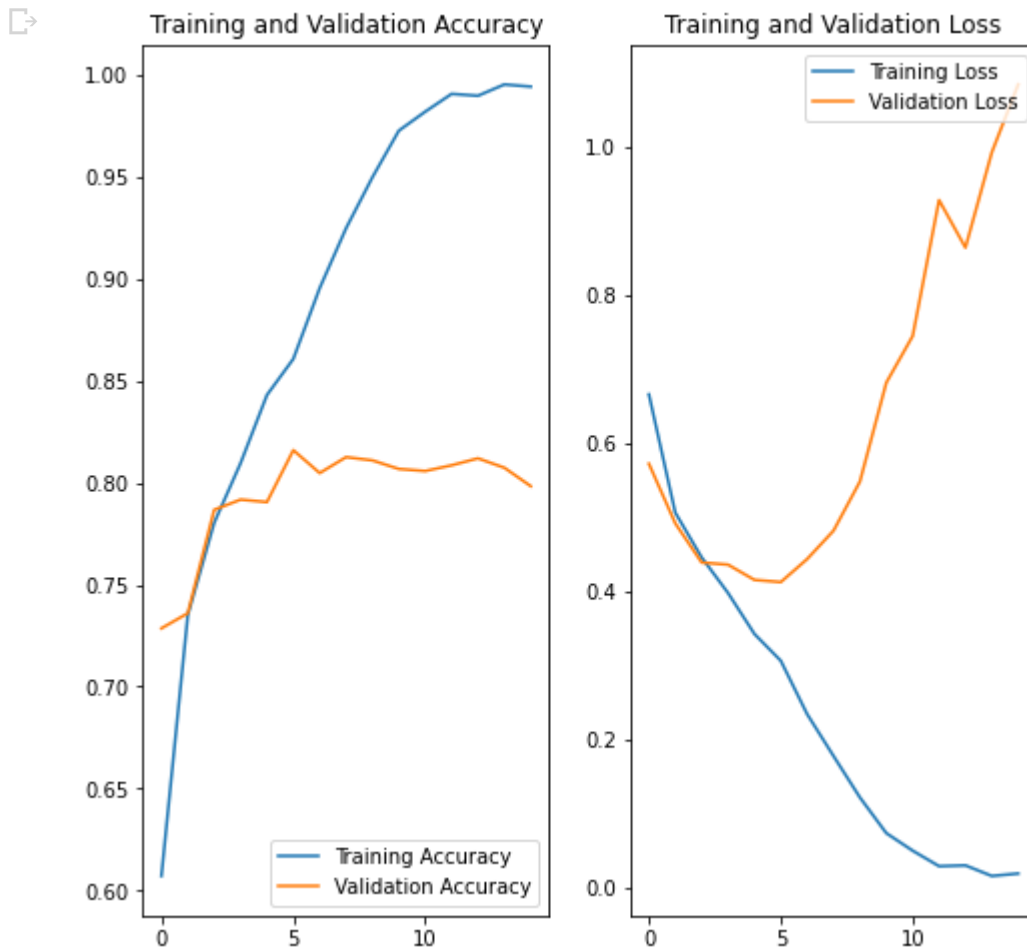
156/156 [=====] - 65s 415ms/step - loss: 0.0194 - accuracy: 0.9

```
1 acc = history.history['accuracy']
2 val_acc = history.history['val_accuracy']
3
4 loss=history.history['loss']
5 val_loss=history.history['val_loss']
6
7 epochs_range = range(epochs)
8
9 plt.figure(figsize=(8, 8))
10 plt.subplot(1, 2, 1)
11 plt.plot(epochs_range, acc, label='Training Accuracy')
12 plt.plot(epochs_range, val_acc, label='Validation Accuracy')
13 plt.legend(loc='lower right')
14 plt.title('Training and Validation Accuracy')
15
16 plt.subplot(1, 2, 2)
17 plt.plot(epochs_range, loss, label='Training Loss')
18 plt.plot(epochs_range, val_loss, label='Validation Loss')
```

```

19 plt.legend(loc='upper right')
20 plt.title('Training and Validation Loss')
21 plt.show()

```



Задание 3. Примените дополнение данных (data augmentation). Как это повлияло на качество

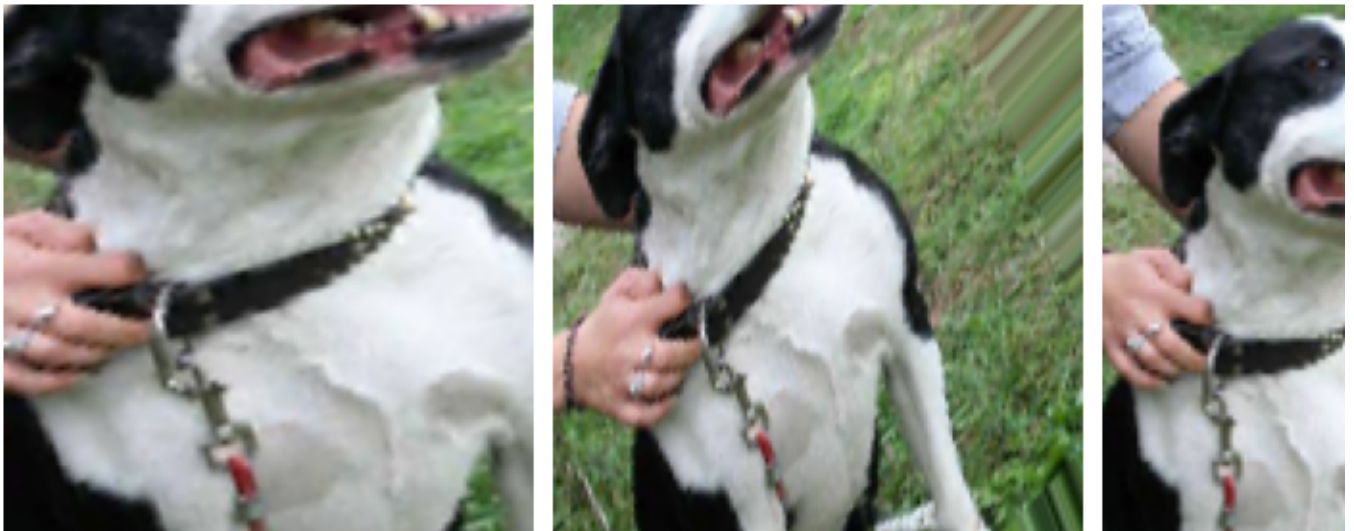
```

1  image_gen_train = ImageDataGenerator(
2      rescale=1./255,
3      rotation_range=45,
4      width_shift_range=.15,
5      height_shift_range=.15,
6      horizontal_flip=True,
7      zoom_range=0.5
8  )
9  train_data_gen = image_gen_train.flow_from_directory(batch_size=batch_size,
10                                                         directory=train_dir,
11                                                         shuffle=True,
12                                                         target_size=(IMG_HEIGHT, IMG_WIDTH),
13                                                         class_mode='binary')
14  augmented_images = [train_data_gen[0][0][0] for i in range(5)]
15  plotImages(augmented_images)

```



Found 20000 images belonging to 2 classes.



```
1 image_gen_val = ImageDataGenerator(rescale=1./255)

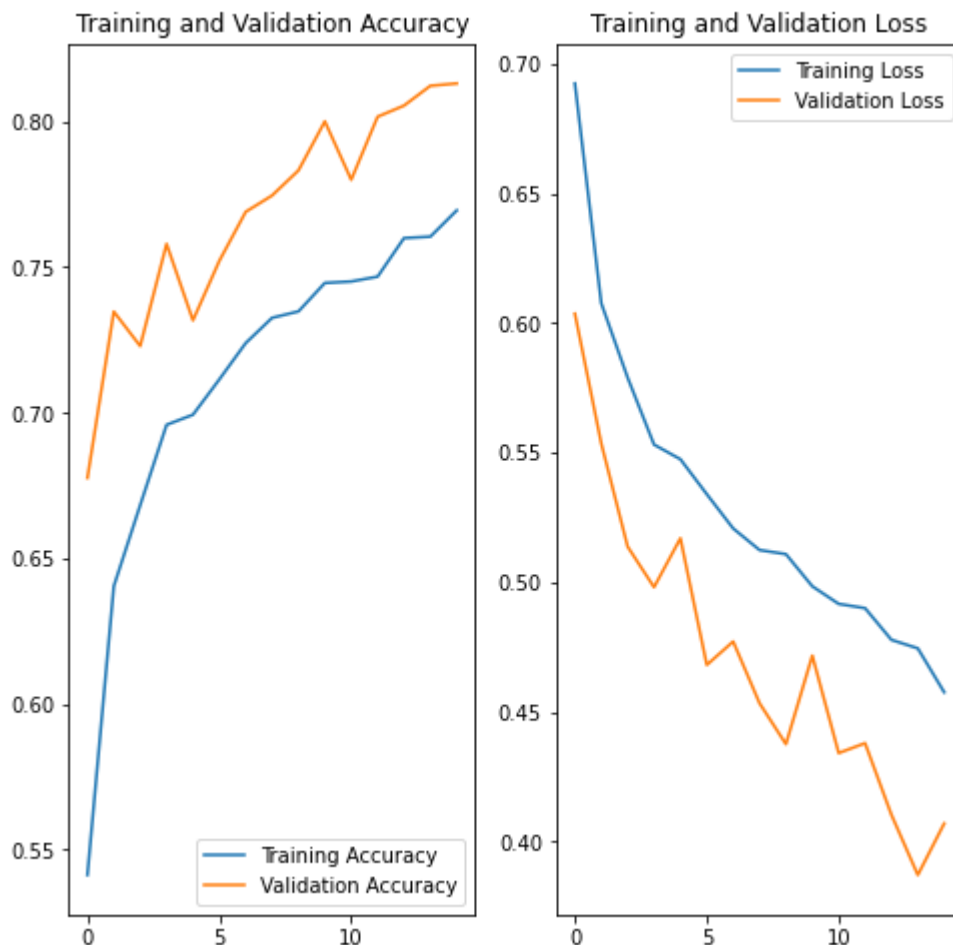
1 val_data_gen = image_gen_val.flow_from_directory(batch_size=batch_size,
2                                                  directory=validation_dir,
3                                                  target_size=(IMG_HEIGHT, IMG_WIDTH),
4                                                  class_mode='binary')
```

Found 5000 images belonging to 2 classes.

```
1 model = Sequential([
2     Conv2D(16, 3, padding='same', activation='relu', input_shape=(IMG_HEIGHT, IMG_WIDTH,
3     MaxPooling2D(),
4     Conv2D(32, 3, padding='same', activation='relu'),
5     MaxPooling2D(),
6     Conv2D(64, 3, padding='same', activation='relu'),
7     MaxPooling2D(),
8     Flatten(),
9     Dense(512, activation='relu'),
10    Dense(1)
11 ])
12 model.compile(optimizer='adam',
13               loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
14               metrics=['accuracy'])
15 model.summary()
16 history = model.fit_generator(
17     train_data_gen,
18     steps_per_epoch=total_train // batch_size,
19     epochs=epochs,
20     validation_data=val_data_gen,
21     validation_steps=total_val // batch_size
22 )
23
```


Model: "sequential_1"

```
1 acc = history.history['accuracy']
2 val_acc = history.history['val_accuracy']
3
4 loss=history.history['loss']
5 val_loss=history.history['val_loss']
6
7 epochs_range = range(epochs)
8
9 plt.figure(figsize=(8, 8))
10 plt.subplot(1, 2, 1)
11 plt.plot(epochs_range, acc, label='Training Accuracy')
12 plt.plot(epochs_range, val_acc, label='Validation Accuracy')
13 plt.legend(loc='lower right')
14 plt.title('Training and Validation Accuracy')
15
16 plt.subplot(1, 2, 2)
17 plt.plot(epochs_range, loss, label='Training Loss')
18 plt.plot(epochs_range, val_loss, label='Validation Loss')
19 plt.legend(loc='upper right')
20 plt.title('Training and Validation Loss')
21 plt.show()
```



156/156 [-----] - 140s 899ms/step - loss: 0.4576 - accuracy: 0

Качество улучшилось

Задание 4. Поэкспериментируйте с готовыми нейронными сетями (например, AlexNet, VGG16, передаточное обучение. Как это повлияло на качество классификатора? Какой максимальный Kaggle? Почему?

```
1  model_new = Sequential([
2      Conv2D(16, 3, padding='same', activation='relu',
3          input_shape=(IMG_HEIGHT, IMG_WIDTH, 3)),
4      MaxPooling2D(),
5      Dropout(0.2),
6      Conv2D(32, 3, padding='same', activation='relu'),
7      MaxPooling2D(),
8      Conv2D(64, 3, padding='same', activation='relu'),
9      MaxPooling2D(),
10     Dropout(0.2),
11     Flatten(),
12     Dense(512, activation='relu'),
13     Dense(1)
14 ])

1  model_new.compile(optimizer='adam',
2                    loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
3                    metrics=['accuracy'])
4
5  model_new.summary()
```



Model: "sequential_2"

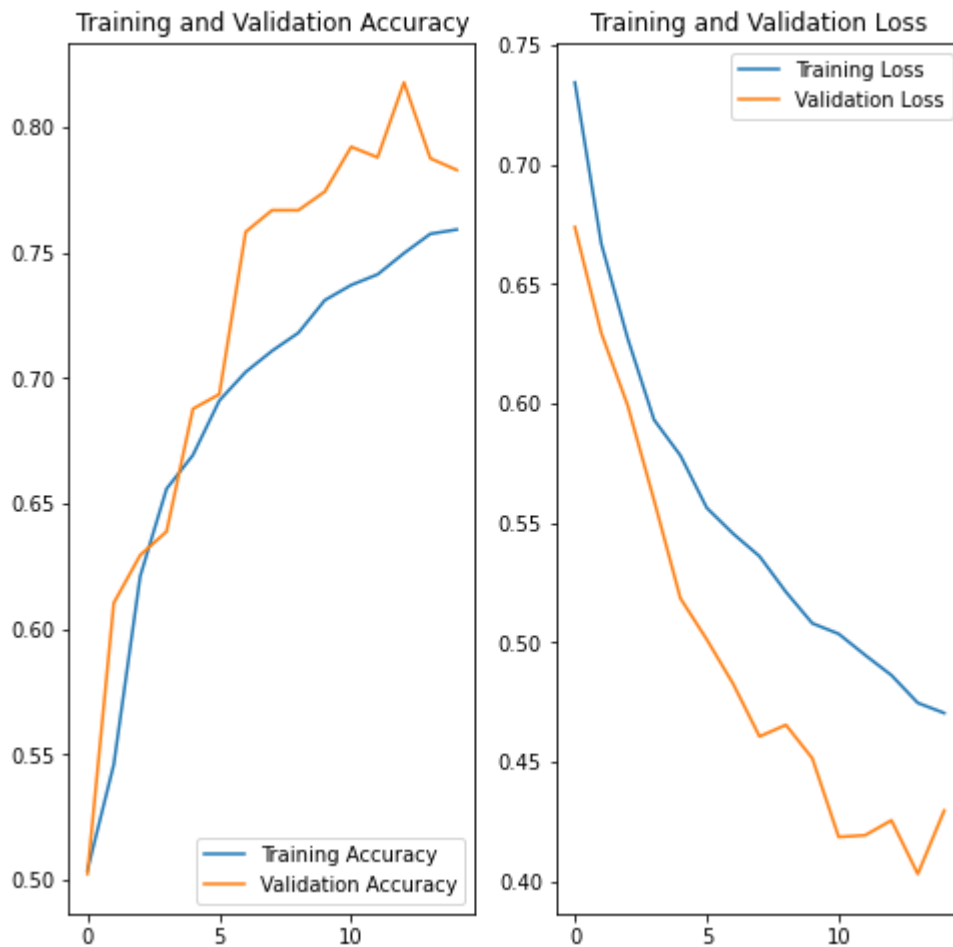
Layer (type)	Output Shape	Param #
=====		
conv2d_6 (Conv2D)	(None, 150, 150, 16)	448
max_pooling2d_6 (MaxPooling2D)	(None, 75, 75, 16)	0
dropout (Dropout)	(None, 75, 75, 16)	0
conv2d_7 (Conv2D)	(None, 75, 75, 32)	4640
max_pooling2d_7 (MaxPooling2D)	(None, 37, 37, 32)	0
conv2d_8 (Conv2D)	(None, 37, 37, 64)	18496
max_pooling2d_8 (MaxPooling2D)	(None, 18, 18, 64)	0
dropout_1 (Dropout)	(None, 18, 18, 64)	0
flatten_2 (Flatten)	(None, 20736)	0
dense_4 (Dense)	(None, 512)	10617344
dense_5 (Dense)	(None, 1)	513
=====		
Total params: 10,641,441		
Trainable params: 10,641,441		
Non-trainable params: 0		

```
1 history = model_new.fit_generator(  
2     train_data_gen,  
3     steps_per_epoch=total_train // batch_size,  
4     epochs=epochs,  
5     validation_data=val_data_gen,  
6     validation_steps=total_val // batch_size  
7 )
```



```
Epoch 1/15
156/156 [=====] - 142s 913ms/step - loss: 0.7345 - accuracy: 0.
Epoch 2/15
156/156 [=====] - 141s 904ms/step - loss: 0.6669 - accuracy: 0.
Epoch 3/15
156/156 [=====] - 142s 908ms/step - loss: 0.6273 - accuracy: 0.
Epoch 4/15
156/156 [=====] - 142s 910ms/step - loss: 0.5932 - accuracy: 0.
Epoch 5/15
156/156 [=====] - 140s 900ms/step - loss: 0.5783 - accuracy: 0.
Epoch 6/15
156/156 [=====] - 141s 905ms/step - loss: 0.5563 - accuracy: 0.
Epoch 7/15
156/156 [=====] - 141s 906ms/step - loss: 0.5455 - accuracy: 0.
Epoch 8/15
156/156 [=====] - 142s 911ms/step - loss: 0.5360 - accuracy: 0.
Epoch 9/15
156/156 [=====] - 142s 910ms/step - loss: 0.5211 - accuracy: 0.
Epoch 10/15
156/156 [=====] - 143s 916ms/step - loss: 0.5080 - accuracy: 0.
Epoch 11/15
156/156 [=====] - 143s 915ms/step - loss: 0.5036 - accuracy: 0.
Epoch 12/15
156/156 [=====] - 145s 930ms/step - loss: 0.4947 - accuracy: 0.
Epoch 13/15
156/156 [=====] - 145s 931ms/step - loss: 0.4862 - accuracy: 0.
Epoch 14/15
156/156 [=====] - 145s 928ms/step - loss: 0.4746 - accuracy: 0.
Epoch 15/15
156/156 [=====] - 144s 924ms/step - loss: 0.4704 - accuracy: 0.
```

```
1  acc = history.history['accuracy']
2  val_acc = history.history['val_accuracy']
3
4  loss = history.history['loss']
5  val_loss = history.history['val_loss']
6
7  epochs_range = range(epochs)
8
9  plt.figure(figsize=(8, 8))
10 plt.subplot(1, 2, 1)
11 plt.plot(epochs_range, acc, label='Training Accuracy')
12 plt.plot(epochs_range, val_acc, label='Validation Accuracy')
13 plt.legend(loc='lower right')
14 plt.title('Training and Validation Accuracy')
15
16 plt.subplot(1, 2, 2)
17 plt.plot(epochs_range, loss, label='Training Loss')
18 plt.plot(epochs_range, val_loss, label='Validation Loss')
19 plt.legend(loc='upper right')
20 plt.title('Training and Validation Loss')
21 plt.show()
```



```
1 from tensorflow.keras.layers import GlobalAveragePooling2D
2 from tensorflow.keras.applications import MobileNet
3 from tensorflow.keras.models import Model
4
5 base_model=MobileNet(weights='imagenet',include_top=False)
6
7 x=base_model.output
8 x=GlobalAveragePooling2D()(x)
9 x=Dense(1024,activation='relu')(x)
10 x=Dense(1024,activation='relu')(x)
11 x=Dense(512,activation='relu')(x)
12 preds=Dense(1,activation='softmax')(x)
13 model=Model(inputs=base_model.input,outputs=preds)
14 model.summary()
15 for layer in model.layers:
16     layer.trainable=False
17 model.compile(optimizer='Adam',loss='binary_crossentropy',metrics=['accuracy'])
18
19 history = model.fit_generator(
20     train_data_gen,
21     steps_per_epoch=total_train // batch_size,
22     epochs=epochs,
23     validation_data=val_data_gen,
24     validation_steps=total_val // batch_size
```

```
24         validation_steps=total_val // batch_size
25     )
```



WARNING:tensorflow:`input_shape` is undefined or non-square, or `rows` is not in [128, 1
Model: "model_1"

Layer (type)	Output Shape	Param #
=====		
input_4 (InputLayer)	[(None, None, None, 3)]	0
conv1_pad (ZeroPadding2D)	(None, None, None, 3)	0
conv1 (Conv2D)	(None, None, None, 32)	864
conv1_bn (BatchNormalization)	(None, None, None, 32)	128
conv1_relu (ReLU)	(None, None, None, 32)	0
conv_dw_1 (DepthwiseConv2D)	(None, None, None, 32)	288
conv_dw_1_bn (BatchNormaliza	(None, None, None, 32)	128
conv_dw_1_relu (ReLU)	(None, None, None, 32)	0
conv_pw_1 (Conv2D)	(None, None, None, 64)	2048
conv_pw_1_bn (BatchNormaliza	(None, None, None, 64)	256
conv_pw_1_relu (ReLU)	(None, None, None, 64)	0
conv_pad_2 (ZeroPadding2D)	(None, None, None, 64)	0
conv_dw_2 (DepthwiseConv2D)	(None, None, None, 64)	576
conv_dw_2_bn (BatchNormaliza	(None, None, None, 64)	256
conv_dw_2_relu (ReLU)	(None, None, None, 64)	0
conv_pw_2 (Conv2D)	(None, None, None, 128)	8192
conv_pw_2_bn (BatchNormaliza	(None, None, None, 128)	512
conv_pw_2_relu (ReLU)	(None, None, None, 128)	0
conv_dw_3 (DepthwiseConv2D)	(None, None, None, 128)	1152
conv_dw_3_bn (BatchNormaliza	(None, None, None, 128)	512
conv_dw_3_relu (ReLU)	(None, None, None, 128)	0
conv_pw_3 (Conv2D)	(None, None, None, 128)	16384
conv_pw_3_bn (BatchNormaliza	(None, None, None, 128)	512
conv_pw_3_relu (ReLU)	(None, None, None, 128)	0
conv_pad_4 (ZeroPadding2D)	(None, None, None, 128)	0
conv_dw_4 (DepthwiseConv2D)	(None, None, None, 128)	1152

conv_dw_4_bn (BatchNormaliza	(None, None, None, 128)	512
conv_dw_4_relu (ReLU)	(None, None, None, 128)	0
conv_pw_4 (Conv2D)	(None, None, None, 256)	32768
conv_pw_4_bn (BatchNormaliza	(None, None, None, 256)	1024
conv_pw_4_relu (ReLU)	(None, None, None, 256)	0
conv_dw_5 (DepthwiseConv2D)	(None, None, None, 256)	2304
conv_dw_5_bn (BatchNormaliza	(None, None, None, 256)	1024
conv_dw_5_relu (ReLU)	(None, None, None, 256)	0
conv_pw_5 (Conv2D)	(None, None, None, 256)	65536
conv_pw_5_bn (BatchNormaliza	(None, None, None, 256)	1024
conv_pw_5_relu (ReLU)	(None, None, None, 256)	0
conv_pad_6 (ZeroPadding2D)	(None, None, None, 256)	0
conv_dw_6 (DepthwiseConv2D)	(None, None, None, 256)	2304
conv_dw_6_bn (BatchNormaliza	(None, None, None, 256)	1024
conv_dw_6_relu (ReLU)	(None, None, None, 256)	0
conv_pw_6 (Conv2D)	(None, None, None, 512)	131072
conv_pw_6_bn (BatchNormaliza	(None, None, None, 512)	2048
conv_pw_6_relu (ReLU)	(None, None, None, 512)	0
conv_dw_7 (DepthwiseConv2D)	(None, None, None, 512)	4608
conv_dw_7_bn (BatchNormaliza	(None, None, None, 512)	2048
conv_dw_7_relu (ReLU)	(None, None, None, 512)	0
conv_pw_7 (Conv2D)	(None, None, None, 512)	262144
conv_pw_7_bn (BatchNormaliza	(None, None, None, 512)	2048
conv_pw_7_relu (ReLU)	(None, None, None, 512)	0
conv_dw_8 (DepthwiseConv2D)	(None, None, None, 512)	4608
conv_dw_8_bn (BatchNormaliza	(None, None, None, 512)	2048
conv_dw_8_relu (ReLU)	(None, None, None, 512)	0
conv_pw_8 (Conv2D)	(None, None, None, 512)	262144
conv_pw_8_bn (BatchNormaliza	(None, None, None, 512)	2048

conv_pw_8_relu (ReLU)	(None, None, None, 512)	0
conv_dw_9 (DepthwiseConv2D)	(None, None, None, 512)	4608
conv_dw_9_bn (BatchNormaliza	(None, None, None, 512)	2048
conv_dw_9_relu (ReLU)	(None, None, None, 512)	0
conv_pw_9 (Conv2D)	(None, None, None, 512)	262144
conv_pw_9_bn (BatchNormaliza	(None, None, None, 512)	2048
conv_pw_9_relu (ReLU)	(None, None, None, 512)	0
conv_dw_10 (DepthwiseConv2D)	(None, None, None, 512)	4608
conv_dw_10_bn (BatchNormaliz	(None, None, None, 512)	2048
conv_dw_10_relu (ReLU)	(None, None, None, 512)	0
conv_pw_10 (Conv2D)	(None, None, None, 512)	262144
conv_pw_10_bn (BatchNormaliz	(None, None, None, 512)	2048
conv_pw_10_relu (ReLU)	(None, None, None, 512)	0
conv_dw_11 (DepthwiseConv2D)	(None, None, None, 512)	4608
conv_dw_11_bn (BatchNormaliz	(None, None, None, 512)	2048
conv_dw_11_relu (ReLU)	(None, None, None, 512)	0
conv_pw_11 (Conv2D)	(None, None, None, 512)	262144
conv_pw_11_bn (BatchNormaliz	(None, None, None, 512)	2048
conv_pw_11_relu (ReLU)	(None, None, None, 512)	0
conv_pad_12 (ZeroPadding2D)	(None, None, None, 512)	0
conv_dw_12 (DepthwiseConv2D)	(None, None, None, 512)	4608
conv_dw_12_bn (BatchNormaliz	(None, None, None, 512)	2048
conv_dw_12_relu (ReLU)	(None, None, None, 512)	0
conv_pw_12 (Conv2D)	(None, None, None, 1024)	524288
conv_pw_12_bn (BatchNormaliz	(None, None, None, 1024)	4096
conv_pw_12_relu (ReLU)	(None, None, None, 1024)	0
conv_dw_13 (DepthwiseConv2D)	(None, None, None, 1024)	9216
conv_dw_13_bn (BatchNormaliz	(None, None, None, 1024)	4096
conv_dw_13_relu (ReLU)	(None, None, None, 1024)	0

conv_pw_13 (Conv2D)	(None, None, None, 1024)	1048576
conv_pw_13_bn (BatchNormaliz	(None, None, None, 1024)	4096
conv_pw_13_relu (ReLU)	(None, None, None, 1024)	0
global_average_pooling2d_2 ((None, 1024)	0
dense_14 (Dense)	(None, 1024)	1049600
dense_15 (Dense)	(None, 1024)	1049600
dense_16 (Dense)	(None, 512)	524800
dense_17 (Dense)	(None, 1)	513
=====		
Total params: 5,853,377		
Trainable params: 5,831,489		
Non-trainable params: 21,888		

```

Epoch 1/15
156/156 [=====] - 148s 949ms/step - loss: 7.5925 - accuracy: 0.
Epoch 2/15
156/156 [=====] - 146s 934ms/step - loss: 7.6391 - accuracy: 0.
Epoch 3/15
156/156 [=====] - 144s 925ms/step - loss: 7.5925 - accuracy: 0.
Epoch 4/15
156/156 [=====] - 144s 926ms/step - loss: 7.6513 - accuracy: 0.
Epoch 5/15
156/156 [=====] - 146s 933ms/step - loss: 7.6628 - accuracy: 0.
Epoch 6/15
156/156 [=====] - 146s 935ms/step - loss: 7.5987 - accuracy: 0.
Epoch 7/15
156/156 [=====] - 147s 941ms/step - loss: 7.6582 - accuracy: 0.
Epoch 8/15
156/156 [=====] - 146s 936ms/step - loss: 7.5987 - accuracy: 0.
Epoch 9/15
156/156 [=====] - 146s 934ms/step - loss: 7.6086 - accuracy: 0.
Epoch 10/15
156/156 [=====] - 144s 925ms/step - loss: 7.6391 - accuracy: 0.
Epoch 11/15
156/156 [=====] - 144s 921ms/step - loss: 7.6071 - accuracy: 0.
Epoch 12/15
156/156 [=====] - 145s 927ms/step - loss: 7.6559 - accuracy: 0.
Epoch 13/15
156/156 [=====] - 145s 932ms/step - loss: 7.6598 - accuracy: 0.
Epoch 14/15
156/156 [=====] - 146s 937ms/step - loss: 7.6032 - accuracy: 0.
Epoch 15/15
156/156 [=====] - 145s 932ms/step - loss: 7.6399 - accuracy: 0.

```

```

1 acc = history.history['accuracy']
2 val_acc = history.history['val_accuracy']

```

```

-     history.history['acc'], history.history['val_acc'],
3
4     loss=history.history['loss']
5     val_loss=history.history['val_loss']
6
7     epochs_range = range(epochs)
8
9     plt.figure(figsize=(8, 8))
10    plt.subplot(1, 2, 1)
11    plt.plot(epochs_range, acc, label='Training Accuracy')
12    plt.plot(epochs_range, val_acc, label='Validation Accuracy')
13    plt.legend(loc='lower right')
14    plt.title('Training and Validation Accuracy')
15
16    plt.subplot(1, 2, 2)
17    plt.plot(epochs_range, loss, label='Training Loss')
18    plt.plot(epochs_range, val_loss, label='Validation Loss')
19    plt.legend(loc='upper right')
20    plt.title('Training and Validation Loss')
21    plt.show()

```



