Importing Libraries

```
from glob import glob
import cv2
from PIL import Image
import numpy as np
from sklearn.metrics import confusion_matrix
import seaborn as sns
from sklearn.model_selection import train_test_split
import tensorflow as tf
import keras
from tensorflow.keras.utils import normalize
from keras.models import Sequential
from tensorflow.keras import Model
from keras.layers import Conv2D, MaxPooling2D
from keras.layers import Activation, Dropout, Flatten, Dense
from keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras import layers
from tensorflow.keras.applications.vgg16 import VGG16
```

connecting with kaggle dir

```
! pip install -q kaggle
from google.colab import files
files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving kaggle.json to kaggle.json
```

```
{'kaggle.json':
b'{"username":"manu0589","key":"781270b7f9a8d0e147c626ae65786ce8"}'}
```

```
! mkdir ~/.kaggle
```

```
! cp kaggle.json ~/.kaggle/
```

```
! chmod 600 ~/.kaggle/kaggle.json
```

Downloading Data

```
!kaggle datasets download -d iarunava/cell-images-for-detecting-
malaria #download dataset from kaggle
```

```
Downloading cell-images-for-detecting-malaria.zip to /content
100% 672M/675M [00:04<00:00, 212MB/s]
100% 675M/675M [00:04<00:00, 162MB/s]
```

```
import os
zip_path = '/content/cell-images-for-detecting-malaria.zip'
```

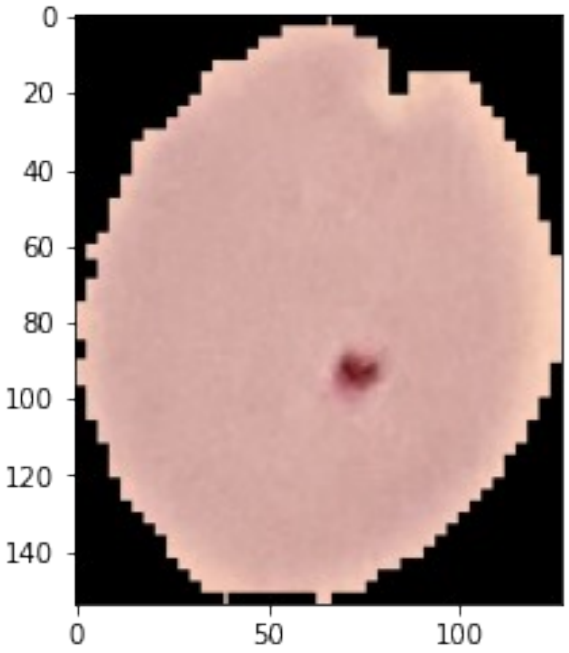
```
from zipfile import ZipFile
with ZipFile(zip_path,'r') as zip:
```

```
  zip.extractall()
  print('Done')
```

```
Done
```

image visualization

```
import matplotlib.pyplot as plt
im =
plt.imread('/content/cell_images/Parasitized/C33P1thinF_IMG_20150619_1
14756a_cell_180.png')
plt.imshow(im)
plt.show()
```




```
pip install split-folders
```

```
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Collecting split-folders
  Downloading split_folders-0.5.1-py3-none-any.whl (8.4 kB)
Installing collected packages: split-folders
Successfully installed split-folders-0.5.1
```

```
!rm -rf '/content/cell_images/cell_images/'
```

Creating Train and Test folders

```
import splitfolders
splitfolders.ratio("/content/cell_images", output="output", seed=1337,
ratio=(.8, .2)) # default values
```

```
Copying files: 27560 files [00:09, 2812.11 files/s]
```

Using image Augmentation

```
train_data = ImageDataGenerator(
    rescale=1./255,
    rotation_range=40,
    fill_mode='nearest',
    width_shift_range=0.2,
    height_shift_range=0.2,
    brightness_range=[0.4,1.5],
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,vertical_flip=True)

test_data = ImageDataGenerator(rescale=1./255)

train_generator = train_data.flow_from_directory(
        "/content/output/train",
        target_size=(150, 150),  # All images will be resized to
150x150
        batch_size=20,
        class_mode='binary')
validation_generator = test_data.flow_from_directory(
        "/content/output/val",
        target_size=(150, 150),
        batch_size=20,
        class_mode='binary')

Found 22046 images belonging to 2 classes.
Found 5512 images belonging to 2 classes.
```

initializing cnn model

```
INPUT_SHAPE = (150, 150, 3)

model = Sequential()
model.add(Conv2D(32, (3, 3), input_shape=INPUT_SHAPE))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Conv2D(32, (3, 3), kernel_initializer = 'he_uniform'))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Conv2D(64, (3, 3), kernel_initializer = 'he_uniform'))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Flatten())
model.add(Dense(64))
model.add(Activation('relu'))
model.add(Dropout(0.5))
```

```
model.add(Dense(1))
model.add(Activation('sigmoid'))

model.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=['acc'])

print(model.summary())
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 148, 148, 32)      896

 activation (Activation)     (None, 148, 148, 32)      0

 max_pooling2d (MaxPooling2D  (None, 74, 74, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 72, 72, 32)        9248

 activation_1 (Activation)   (None, 72, 72, 32)        0

 max_pooling2d_1 (MaxPooling  (None, 36, 36, 32)       0
 2D)

 conv2d_2 (Conv2D)           (None, 34, 34, 64)        18496

 activation_2 (Activation)   (None, 34, 34, 64)        0

 max_pooling2d_2 (MaxPooling  (None, 17, 17, 64)       0
 2D)

 flatten (Flatten)           (None, 18496)             0

 dense (Dense)               (None, 64)                1183808

 activation_3 (Activation)   (None, 64)                0

 dropout (Dropout)           (None, 64)                0

 dense_1 (Dense)             (None, 1)                 65

 activation_4 (Activation)   (None, 1)                 0

=================================================================
Total params: 1,212,513
Trainable params: 1,212,513
Non-trainable params: 0
```

```
_________________________________________________________________
None
```

Model training

```
history = model.fit_generator(
     train_generator,
     steps_per_epoch=100,  # 2000 images = batch_size * steps
     epochs=15,
     validation_data=validation_generator,
     validation_steps=50,  # 1000 images = batch_size * steps
     verbose=2)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:7:
UserWarning: `Model.fit_generator` is deprecated and will be removed
in a future version. Please use `Model.fit`, which supports
generators.
  import sys

Epoch 1/15
100/100 - 28s - loss: 0.7101 - acc: 0.5615 - val_loss: 0.6811 -
val_acc: 0.5930 - 28s/epoch - 281ms/step
Epoch 2/15
100/100 - 17s - loss: 0.6827 - acc: 0.5590 - val_loss: 0.6902 -
val_acc: 0.5830 - 17s/epoch - 169ms/step
Epoch 3/15
100/100 - 16s - loss: 0.6930 - acc: 0.5070 - val_loss: 0.6919 -
val_acc: 0.5060 - 16s/epoch - 164ms/step
Epoch 4/15
100/100 - 15s - loss: 0.6926 - acc: 0.5210 - val_loss: 0.6890 -
val_acc: 0.5160 - 15s/epoch - 148ms/step
Epoch 5/15
100/100 - 17s - loss: 0.6442 - acc: 0.6435 - val_loss: 0.6972 -
val_acc: 0.9110 - 17s/epoch - 169ms/step
Epoch 6/15
100/100 - 15s - loss: 0.6599 - acc: 0.5620 - val_loss: 0.6889 -
val_acc: 0.5180 - 15s/epoch - 153ms/step
Epoch 7/15
100/100 - 15s - loss: 0.6945 - acc: 0.5200 - val_loss: 0.6749 -
val_acc: 0.5190 - 15s/epoch - 155ms/step
Epoch 8/15
100/100 - 15s - loss: 0.6238 - acc: 0.6475 - val_loss: 0.5372 -
val_acc: 0.8280 - 15s/epoch - 154ms/step
Epoch 9/15
100/100 - 16s - loss: 0.5426 - acc: 0.7970 - val_loss: 0.4285 -
val_acc: 0.8650 - 16s/epoch - 161ms/step
Epoch 10/15
100/100 - 15s - loss: 0.5097 - acc: 0.8230 - val_loss: 0.3294 -
val_acc: 0.9020 - 15s/epoch - 150ms/step
Epoch 11/15
100/100 - 16s - loss: 0.4557 - acc: 0.8420 - val_loss: 0.3777 -
val_acc: 0.8540 - 16s/epoch - 165ms/step
```

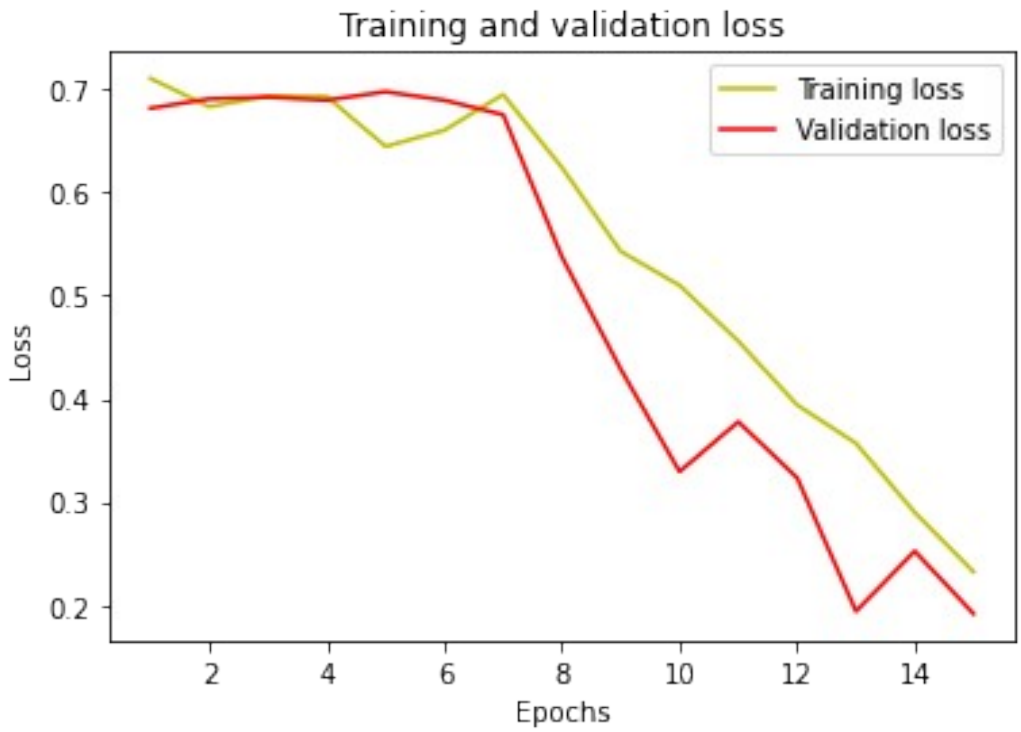
```
Epoch 12/15
100/100 - 15s - loss: 0.3939 - acc: 0.8615 - val_loss: 0.3234 -
val_acc: 0.9000 - 15s/epoch - 150ms/step
Epoch 13/15
100/100 - 15s - loss: 0.3569 - acc: 0.8795 - val_loss: 0.1942 -
val_acc: 0.9550 - 15s/epoch - 148ms/step
Epoch 14/15
100/100 - 18s - loss: 0.2898 - acc: 0.9055 - val_loss: 0.2524 -
val_acc: 0.9400 - 18s/epoch - 177ms/step
Epoch 15/15
100/100 - 17s - loss: 0.2324 - acc: 0.9195 - val_loss: 0.1918 -
val_acc: 0.9410 - 17s/epoch - 167ms/step
```

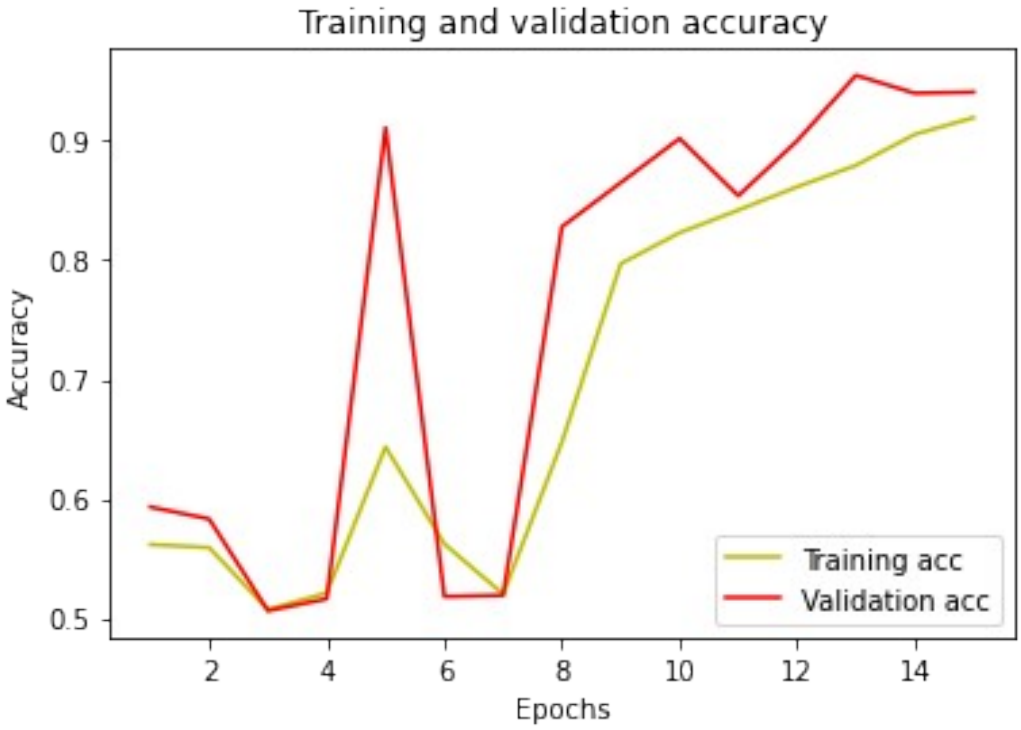
```
model.save('models/malaria_model_100epochs.h5')
```

visualization of training and validation loss and accuracy

```
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(loss) + 1)
plt.plot(epochs, loss, 'y', label='Training loss')
plt.plot(epochs, val_loss, 'r', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

```
acc = history.history['acc']
val_acc = history.history['val_acc']
plt.plot(epochs, acc, 'y', label='Training acc')
plt.plot(epochs, val_acc, 'r', label='Validation acc')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```





Binary class classification Using Transfer Learning Model Vgg16

```
train_data = ImageDataGenerator(
    rescale=1./255,
    rotation_range=40,
```

```
    fill_mode='nearest',
    width_shift_range=0.2,
    height_shift_range=0.2,
    brightness_range=[0.4,1.5],
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,vertical_flip=True)

test_data = ImageDataGenerator(rescale=1./255)

train_generator_vgg = train_data.flow_from_directory(
        "/content/output/train",
        target_size=(224, 224),  # All images will be resized to
150x150
        batch_size=20,
        class_mode='binary')
validation_generator_vgg = test_data.flow_from_directory(
        "/content/output/val",
        target_size=(224, 224),
        batch_size=20,
        class_mode='binary')

Found 22046 images belonging to 2 classes.
Found 5512 images belonging to 2 classes.

tf.keras.backend.clear_session()

model = VGG16(input_shape = (224, 224, 3), # Shape of our images
include_top = False, # Leave out the last fully connected layer
weights = 'imagenet')

for layer in model.layers:
    layer.trainable = False

x = layers.Flatten()(model.output)
# Add a fully connected layer with 512 hidden units and ReLU
activation
x = layers.Dense(512, activation='relu')(x)
# Add a dropout rate of 0.5
x = layers.Dropout(0.5)(x)
# Add a final sigmoid layer for classification
x = layers.Dense(1, activation='sigmoid')(x)
my_model = tf.keras.models.Model(model.input, x)
# Compile the model

# model summary
my_model.summary()

Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
```

```
=================================================================
 input_1 (InputLayer)        [(None, 224, 224, 3)]     0

 block1_conv1 (Conv2D)       (None, 224, 224, 64)      1792

 block1_conv2 (Conv2D)       (None, 224, 224, 64)      36928

 block1_pool (MaxPooling2D)  (None, 112, 112, 64)      0

 block2_conv1 (Conv2D)       (None, 112, 112, 128)     73856

 block2_conv2 (Conv2D)       (None, 112, 112, 128)     147584

 block2_pool (MaxPooling2D)  (None, 56, 56, 128)       0

 block3_conv1 (Conv2D)       (None, 56, 56, 256)       295168

 block3_conv2 (Conv2D)       (None, 56, 56, 256)       590080

 block3_conv3 (Conv2D)       (None, 56, 56, 256)       590080

 block3_pool (MaxPooling2D)  (None, 28, 28, 256)       0

 block4_conv1 (Conv2D)       (None, 28, 28, 512)       1180160

 block4_conv2 (Conv2D)       (None, 28, 28, 512)       2359808

 block4_conv3 (Conv2D)       (None, 28, 28, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 14, 14, 512)       0

 block5_conv1 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_conv2 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_conv3 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_pool (MaxPooling2D)  (None, 7, 7, 512)         0

 flatten (Flatten)           (None, 25088)             0

 dense (Dense)               (None, 512)               12845568

 dropout (Dropout)           (None, 512)               0

 dense_1 (Dense)             (None, 1)                 513

=================================================================
Total params: 27,560,769
Trainable params: 12,846,081
```

```
Non-trainable params: 14,714,688
_________________________________________________________________
```

```
my_model.compile(optimizer = 'adam', loss =
'binary_crossentropy',metrics = ['accuracy'])

model_checkpoint=tf.keras.callbacks.ModelCheckpoint('malaria_model_100
epochs_vgg16.h5',

save_best_only=True,

monitor='val_accuracy',
                                                    mode='max',
                                                    verbose=1)

history = my_model.fit_generator(
     train_generator_vgg,
     steps_per_epoch=100,  # 2000 images = batch_size * steps
     epochs=15,
     validation_data=validation_generator_vgg,
     validation_steps=50,  # 1000 images = batch_size * steps
     verbose=2, callbacks=[model_checkpoint])
```

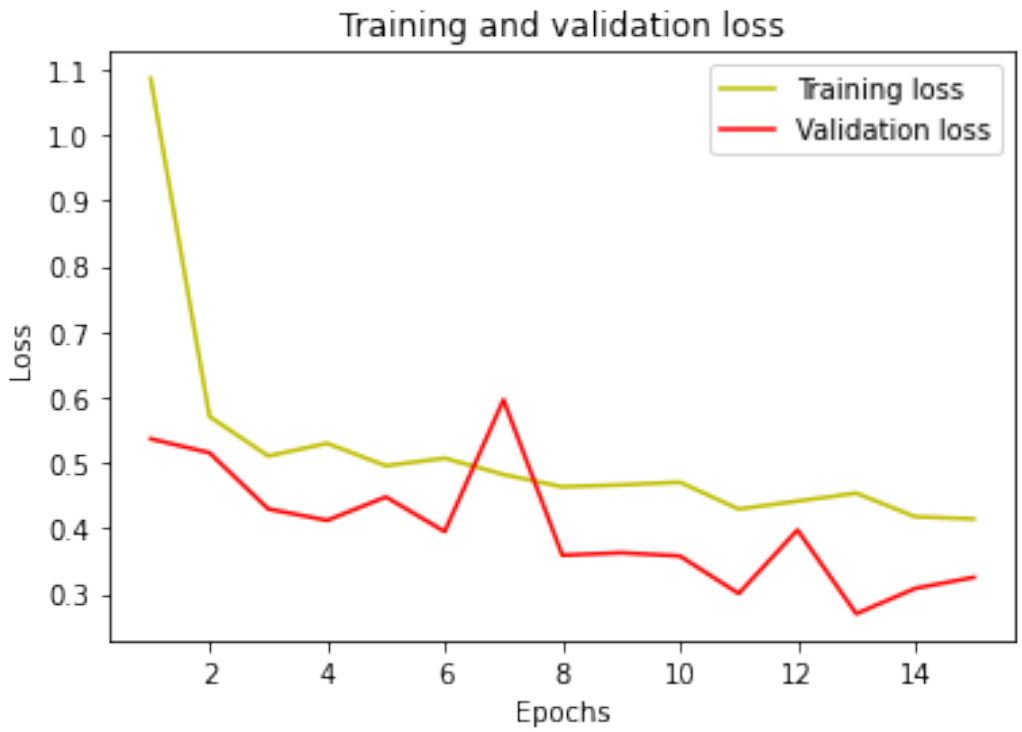
```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:7:
UserWarning: `Model.fit_generator` is deprecated and will be removed
in a future version. Please use `Model.fit`, which supports
generators.
  import sys

Epoch 1/15

Epoch 1: val_accuracy improved from -inf to 0.81900, saving model to
malaria_model_100epochs_vgg16.h5
100/100 - 36s - loss: 1.0860 - accuracy: 0.6210 - val_loss: 0.5363 -
val_accuracy: 0.8190 - 36s/epoch - 360ms/step
Epoch 2/15

Epoch 2: val_accuracy did not improve from 0.81900
100/100 - 35s - loss: 0.5703 - accuracy: 0.7125 - val_loss: 0.5151 -
val_accuracy: 0.7340 - 35s/epoch - 346ms/step
Epoch 3/15

Epoch 3: val_accuracy improved from 0.81900 to 0.85200, saving model
to malaria_model_100epochs_vgg16.h5
100/100 - 35s - loss: 0.5103 - accuracy: 0.7455 - val_loss: 0.4295 -
val_accuracy: 0.8520 - 35s/epoch - 353ms/step
Epoch 4/15

Epoch 4: val_accuracy improved from 0.85200 to 0.86000, saving model
to malaria_model_100epochs_vgg16.h5
100/100 - 36s - loss: 0.5294 - accuracy: 0.7440 - val_loss: 0.4121 -
```

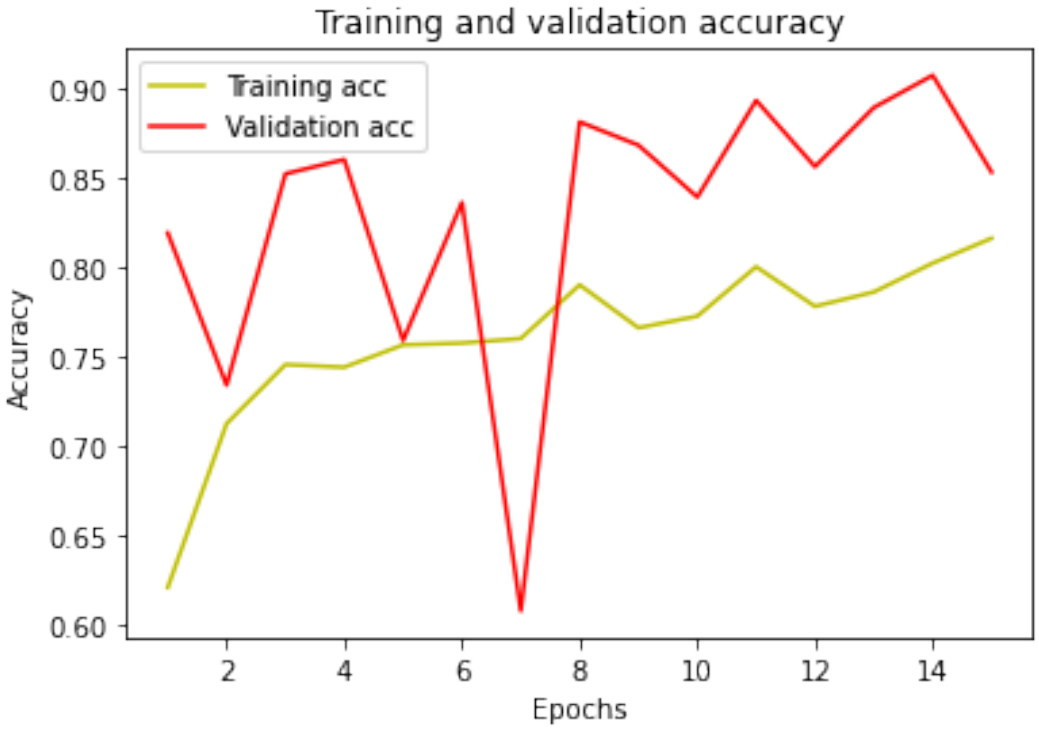
```
val_accuracy: 0.8600 - 36s/epoch - 361ms/step
Epoch 5/15

Epoch 5: val_accuracy did not improve from 0.86000
100/100 - 37s - loss: 0.4954 - accuracy: 0.7565 - val_loss: 0.4479 -
val_accuracy: 0.7590 - 37s/epoch - 365ms/step
Epoch 6/15

Epoch 6: val_accuracy did not improve from 0.86000
100/100 - 36s - loss: 0.5069 - accuracy: 0.7575 - val_loss: 0.3950 -
val_accuracy: 0.8360 - 36s/epoch - 359ms/step
Epoch 7/15

Epoch 7: val_accuracy did not improve from 0.86000
100/100 - 35s - loss: 0.4820 - accuracy: 0.7600 - val_loss: 0.5959 -
val_accuracy: 0.6080 - 35s/epoch - 348ms/step
Epoch 8/15

Epoch 8: val_accuracy improved from 0.86000 to 0.88100, saving model
to malaria_model_100epochs_vgg16.h5
100/100 - 35s - loss: 0.4633 - accuracy: 0.7900 - val_loss: 0.3590 -
val_accuracy: 0.8810 - 35s/epoch - 354ms/step
Epoch 9/15

Epoch 9: val_accuracy did not improve from 0.88100
100/100 - 36s - loss: 0.4662 - accuracy: 0.7660 - val_loss: 0.3627 -
val_accuracy: 0.8680 - 36s/epoch - 355ms/step
Epoch 10/15

Epoch 10: val_accuracy did not improve from 0.88100
100/100 - 35s - loss: 0.4702 - accuracy: 0.7725 - val_loss: 0.3577 -
val_accuracy: 0.8390 - 35s/epoch - 350ms/step
Epoch 11/15

Epoch 11: val_accuracy improved from 0.88100 to 0.89300, saving model
to malaria_model_100epochs_vgg16.h5
100/100 - 36s - loss: 0.4293 - accuracy: 0.8001 - val_loss: 0.3006 -
val_accuracy: 0.8930 - 36s/epoch - 357ms/step
Epoch 12/15

Epoch 12: val_accuracy did not improve from 0.89300
100/100 - 35s - loss: 0.4414 - accuracy: 0.7780 - val_loss: 0.3975 -
val_accuracy: 0.8560 - 35s/epoch - 347ms/step
Epoch 13/15

Epoch 13: val_accuracy did not improve from 0.89300
100/100 - 36s - loss: 0.4536 - accuracy: 0.7860 - val_loss: 0.2698 -
val_accuracy: 0.8890 - 36s/epoch - 364ms/step
Epoch 14/15
```

```
Epoch 14: val_accuracy improved from 0.89300 to 0.90700, saving model
to malaria_model_100epochs_vgg16.h5
100/100 - 35s - loss: 0.4177 - accuracy: 0.8021 - val_loss: 0.3084 -
val_accuracy: 0.9070 - 35s/epoch - 350ms/step
Epoch 15/15

Epoch 15: val_accuracy did not improve from 0.90700
100/100 - 37s - loss: 0.4143 - accuracy: 0.8160 - val_loss: 0.3253 -
val_accuracy: 0.8530 - 37s/epoch - 367ms/step
```

```
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(loss) + 1)
plt.plot(epochs, loss, 'y', label='Training loss')
plt.plot(epochs, val_loss, 'r', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
plt.plot(epochs, acc, 'y', label='Training acc')
plt.plot(epochs, val_acc, 'r', label='Validation acc')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```


Training and validation loss
Training loss
Validation loss
Loss
Epochs
1.1
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
2
4
6
8
10
12
14


Training and validation accuracy
Training acc
Validation acc
Accuracy
Epochs
0.90
0.85
0.80
0.75
0.70
0.65
0.60
2
4
6
8
10
12
14