Malaria Detection (CNN)

March 22, 2020

Malaria Detection with test accuracy of 95%, without Image Augumentation

Importing Libraries

[1]:

```
from PIL import Image
import numpy as np
import os
import cv2
import keras
from keras.utils import np_utils
from sklearn.model_selection import train_test_split
from keras.preprocessing.image import ImageDataGenerator
import tensorflow.keras.layers as Layers
import tensorflow.keras.models as Models
import tensorflow.keras.optimizers as Optimizers
import sklearn.utils as shuffle
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

```
Using TensorFlow backend.
```

Parasitized is given the label of 0 and Uninfected is given the label of 1

[2]:

```
Images = []
Labels = []
Parasitized = os.listdir("../input/cell-images-for-detecting-malaria/
 ↪cell_images/Parasitized/")
for p in Parasitized:
    try:
        image = cv2.imread("../input/cell-images-for-detecting-malaria/
 ↪cell_images/Parasitized/" + p)
        images = Image.fromarray(image, 'RGB')
        images = images.resize((150,150))
        Images.append(np.array(images))
        Labels.append(0)
    except AttributeError:
        print('')
```

```
Uninfected = os.listdir("../input/cell-images-for-detecting-malaria/cell_images/
 ↪Uninfected/")
for u in Uninfected:
    try:
        image = cv2.imread("../input/cell-images-for-detecting-malaria/
 ↪cell_images/Uninfected/" + u)
        images = Image.fromarray(image, 'RGB')
        images = images.resize((150,150))
        Images.append(np.array(images))
        Labels.append(1)
    except AttributeError:
        print('')
```

[3]:

```
Images = np.array(Images)
Labels = np.array(Labels)
```

[4]:

```
print(Images.shape)
print(Labels.shape)
```

```
(27558, 150, 150, 3)
(27558,)
```

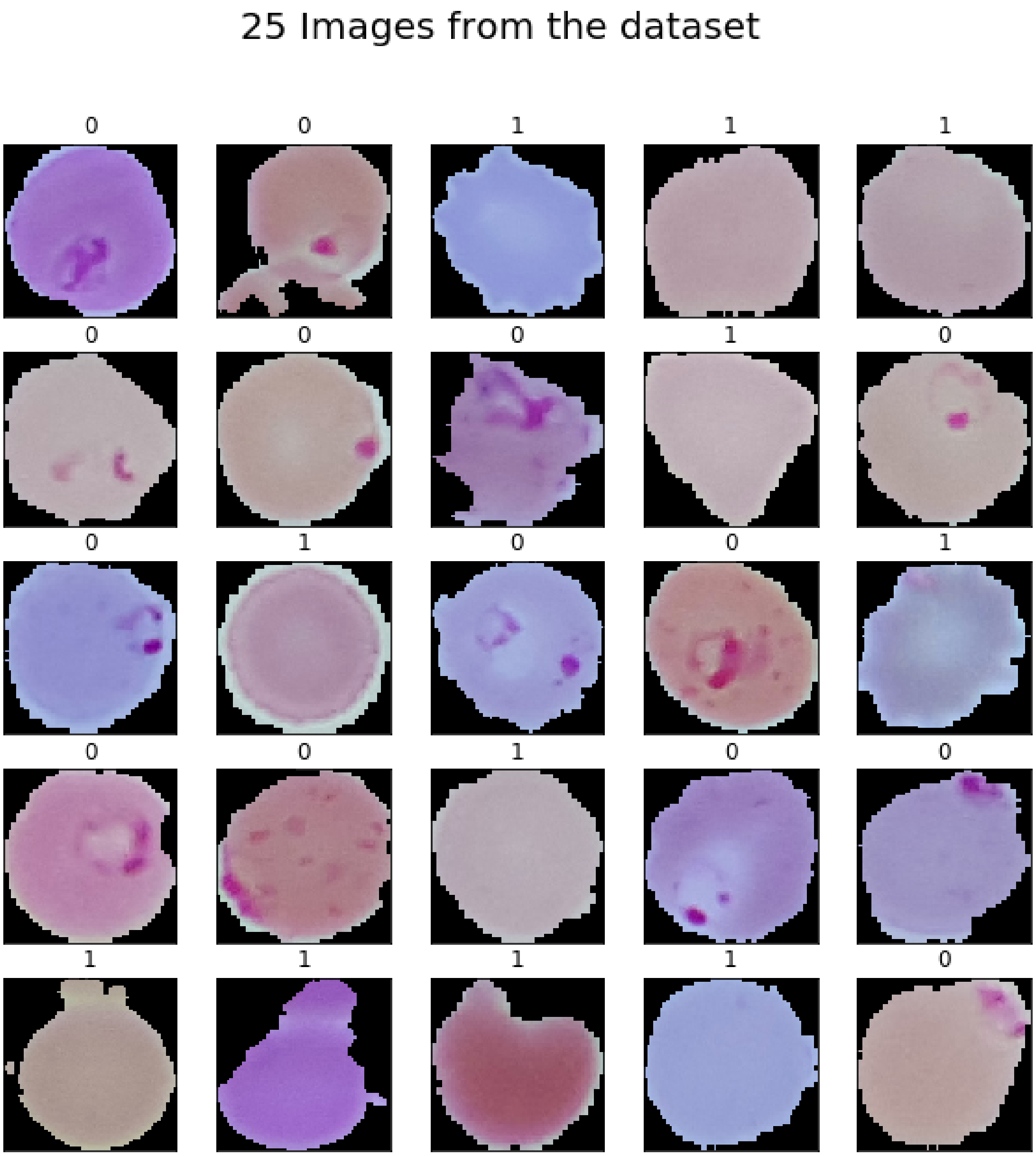
[5]:

```
def show_images(image, label):
    fig = plt.figure(figsize = (10,10))
    fig.suptitle('25 Images from the dataset' ,fontsize = 20)
    for i in range(25):
        index = np.random.randint(Images.shape[0])
        plt.subplot(5,5,i+1)
        plt.imshow(image[index])
        plt.xticks([]) #Scale doesn't appear
        plt.yticks([]) #Scale doesn't apper
        plt.title((label[index]))
        plt.grid(False)
    plt.show()
```

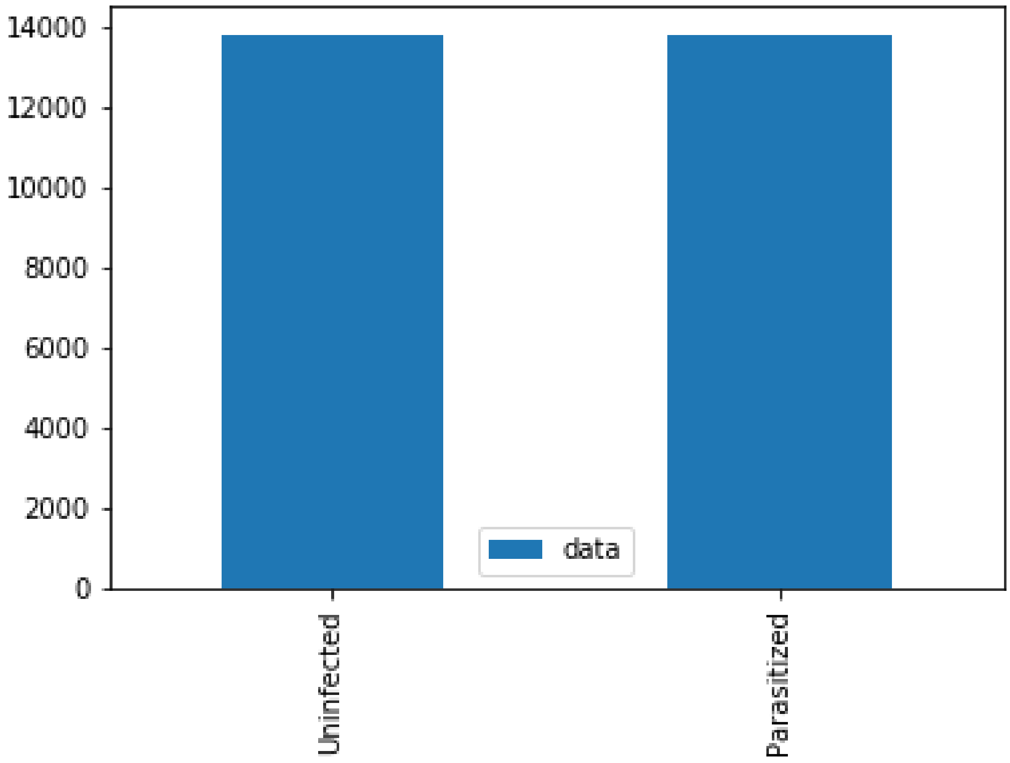
Displaying Images from the dataset

[6]:

```
show_images(Images, Labels)
```



```
[7]: category = ['Uninfected', 'Parasitized']
     _,count = np.unique(Labels, return_counts = True)
     pd.DataFrame({'data': count}, index = category).plot.bar()
     plt.show()
```



[8]:
```
Labels = keras.utils.to_categorical(Labels, 2)
```

[9]:
```
train_x,test_x, train_y, test_y = train_test_split(Images,Labels, test_size = 0.
↪4, random_state = 100)
```

CNN Network

[19]:
```
model = Models.Sequential()
model.add(Layers.Conv2D(64, kernel_size = (3,3), activation = 'relu',␣
↪input_shape = (150,150,3)))
model.add(Layers.Conv2D(64, kernel_size = (3,3), activation = 'relu'))
model.add(Layers.MaxPool2D(3,3))
model.add(Layers.Dropout(0.2))
model.add(Layers.Conv2D(64, kernel_size = (3,3) , activation = 'relu'))
model.add(Layers.Conv2D(64, kernel_size = (3,3) , activation = 'relu'))
model.add(Layers.MaxPool2D(3,3))
model.add(Layers.Conv2D(64, kernel_size = (3,3) , activation = 'relu'))
model.add(Layers.Conv2D(64, kernel_size = (3,3) , activation = 'relu'))
model.add(Layers.MaxPool2D(3,3))
model.add(Layers.Flatten())
model.add(Layers.Dense(512, activation = 'relu'))
model.add(Layers.Dense(256, activation = 'relu'))
model.add(Layers.Dropout(0.2))
model.add(Layers.Dense(2, activation = 'softmax'))
model.compile(optimizer = Optimizers.RMSprop(lr=0.0001), loss =␣
 ↪'categorical_crossentropy', metrics = ['accuracy'])
model.summary()
```

```
Model: "sequential_3"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_20 (Conv2D)           (None, 148, 148, 64)      1792

_________________________________________________________________
conv2d_21 (Conv2D)           (None, 146, 146, 64)      36928

_________________________________________________________________
max_pooling2d_9 (MaxPooling2 (None, 48, 48, 64)        0

_________________________________________________________________
dropout_5 (Dropout)          (None, 48, 48, 64)        0

_________________________________________________________________
conv2d_22 (Conv2D)           (None, 46, 46, 64)        36928

_________________________________________________________________
conv2d_23 (Conv2D)           (None, 44, 44, 64)        36928

_________________________________________________________________
max_pooling2d_10 (MaxPooling (None, 14, 14, 64)        0

_________________________________________________________________
conv2d_24 (Conv2D)           (None, 12, 12, 64)        36928

_________________________________________________________________
conv2d_25 (Conv2D)           (None, 10, 10, 64)        36928

_________________________________________________________________
max_pooling2d_11 (MaxPooling (None, 3, 3, 64)          0

_________________________________________________________________
flatten_2 (Flatten)          (None, 576)               0

_________________________________________________________________
dense_6 (Dense)              (None, 512)               295424

_________________________________________________________________
dense_7 (Dense)              (None, 256)               131328

_________________________________________________________________
dropout_6 (Dropout)          (None, 256)               0

_________________________________________________________________
dense_8 (Dense)              (None, 2)                 514
=================================================================
Total params: 613,698
Trainable params: 613,698
Non-trainable params: 0

_________________________________________________________________
```

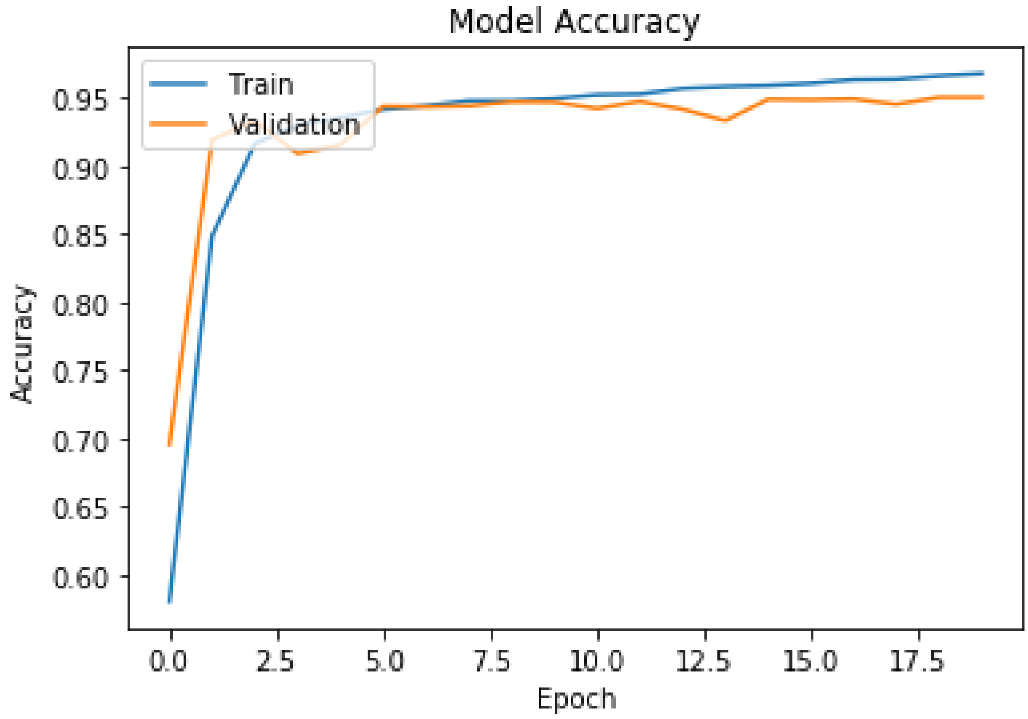
[20]:

```
trained = model.fit(train_x, train_y, epochs = 20, batch_size = 50,␣
 ↪validation_split = 0.20, verbose = 1)
```

```
Train on 13227 samples, validate on 3307 samples
Epoch 1/20
13227/13227 [==============================] - 18s 1ms/sample - loss: 0.7791 -
accuracy: 0.5800 - val_loss: 0.5869 - val_accuracy: 0.6955
Epoch 2/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.3705 -
accuracy: 0.8486 - val_loss: 0.2814 - val_accuracy: 0.9196
Epoch 3/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.2445 -
accuracy: 0.9167 - val_loss: 0.2338 - val_accuracy: 0.9335
Epoch 4/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.2124 -
accuracy: 0.9301 - val_loss: 0.2826 - val_accuracy: 0.9093
Epoch 5/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.1913 -
accuracy: 0.9356 - val_loss: 0.2750 - val_accuracy: 0.9156
Epoch 6/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.1740 -
accuracy: 0.9419 - val_loss: 0.1739 - val_accuracy: 0.9441
Epoch 7/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.1667 -
accuracy: 0.9445 - val_loss: 0.1882 - val_accuracy: 0.9438
Epoch 8/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.1578 -
accuracy: 0.9481 - val_loss: 0.1742 - val_accuracy: 0.9444
Epoch 9/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.1524 -
accuracy: 0.9482 - val_loss: 0.1576 - val_accuracy: 0.9474
Epoch 10/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.1441 -
accuracy: 0.9497 - val_loss: 0.1639 - val_accuracy: 0.9471
Epoch 11/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.1387 -
accuracy: 0.9525 - val_loss: 0.1719 - val_accuracy: 0.9425
Epoch 12/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.1331 -
accuracy: 0.9531 - val_loss: 0.1526 - val_accuracy: 0.9477
Epoch 13/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.1248 -
accuracy: 0.9572 - val_loss: 0.2376 - val_accuracy: 0.9419
Epoch 14/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.1208 -
accuracy: 0.9586 - val_loss: 0.2680 - val_accuracy: 0.9335
Epoch 15/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.1145 -
accuracy: 0.9594 - val_loss: 0.1925 - val_accuracy: 0.9492
Epoch 16/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.1130 -
```

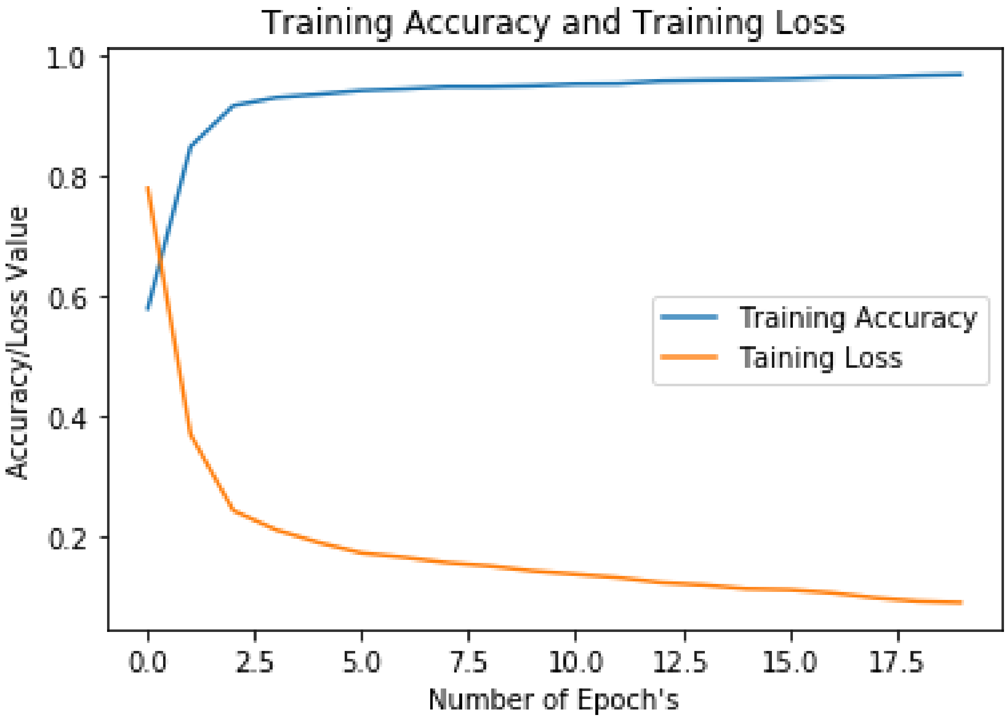
```
accuracy: 0.9609 - val_loss: 0.1775 - val_accuracy: 0.9489
Epoch 17/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.1077 -
accuracy: 0.9635 - val_loss: 0.1929 - val_accuracy: 0.9495
Epoch 18/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.0995 -
accuracy: 0.9639 - val_loss: 0.2079 - val_accuracy: 0.9456
Epoch 19/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.0939 -
accuracy: 0.9664 - val_loss: 0.1993 - val_accuracy: 0.9507
Epoch 20/20
13227/13227 [==============================] - 17s 1ms/sample - loss: 0.0917 -
accuracy: 0.9680 - val_loss: 0.2148 - val_accuracy: 0.9507
```

```
[21]: plt.plot(trained.history['accuracy'])
      plt.plot(trained.history['val_accuracy'])
      plt.title("Model Accuracy")
      plt.ylabel("Accuracy")
      plt.xlabel("Epoch")
      plt.legend(["Train", "Validation"], loc = "upper left")
      plt.show()
```



[27]:

```
plt.plot(range(20), trained.history['accuracy'], label = 'Training Accuracy')
plt.plot(range(20), trained.history['loss'], label = 'Taining Loss')
plt.xlabel("Number of Epoch's")
plt.ylabel('Accuracy/Loss Value')
plt.title('Training Accuracy and Training Loss')
plt.legend(loc = "best")
plt.show()
```



[22]:

```
result = model.evaluate(test_x,test_y,verbose = 1)
```

```
11024/11024 [==============================] - 5s 436us/sample - loss: 0.2107 -
accuracy: 0.9501
```

[23]:

```
print("Test Accuracy: " , result[1] * 100)
```

```
Test Accuracy:  95.01088261604309
```

In few days I will update the kernel with Image Augumentation to improve the results