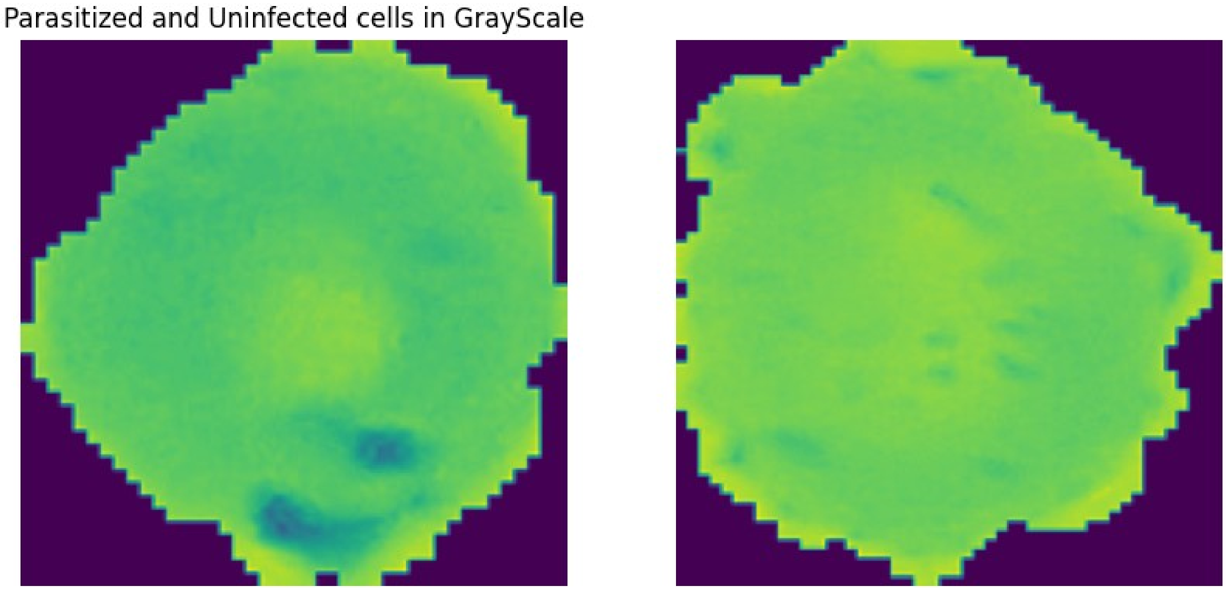
CNN MODEL

```
import os
import cv2
import warnings
import numpy as np
from PIL import Image
import seaborn as sns
from keras.utils import normalize
from keras.models import Sequential
from keras.callbacks import EarlyStopping
from keras.layers import Conv2D, Dense, Dropout, MaxPooling2D, Flatten

import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, precision_score, recall_score,
f1_score, classification_report
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix



warnings.filterwarnings('ignore')

img_dir= "Data/cell_images/"
img_size= 150
dataset = []
label = []

parasite_imgs = os.listdir(img_dir + "Parasitized/")
for i, img_name in enumerate(parasite_imgs):

    if (img_name.split('.')[1] == 'png'):
        img = cv2.imread(img_dir + 'Parasitized/' + img_name,
cv2.IMREAD_GRAYSCALE)
        img = Image.fromarray(img)
        img = img.resize((img_size, img_size))
        demo_imgP = img
        dataset.append(np.array(img))
        label.append(1)


uninfected_imgs = os.listdir(img_dir + "Uninfected/")
for i, img_name in enumerate(uninfected_imgs):

    if (img_name.split('.')[1] == 'png'):
        img = cv2.imread(img_dir + 'Uninfected/' + img_name,
cv2.IMREAD_GRAYSCALE)
        img = Image.fromarray(img)
        img = img.resize((img_size, img_size))
        demo_imgU = img
        dataset.append(np.array(img))
        label.append(0)

dataset = np.array(dataset)
label = np.array(label)


print("Dataset size is ", dataset.shape)
print("Label size is ", label.shape)
demo_imgP=np.asarray(demo_imgP)
demo_imgU=np.asarray(demo_imgU)
plt.figure(figsize=(10,10))
plt.subplot(1, 2, 1)
plt.imshow(demo_imgP)
plt.axis('off')
plt.title("Parasitized and Uninfected cells in GrayScale")
plt.subplot(1, 2, 2)
plt.imshow(demo_imgU)
plt.axis('off')
```

```
Dataset size is  (27558, 150, 150)
Label size is  (27558,)
```

```
(-0.5, 149.5, 149.5, -0.5)
```



```
X_train, X_test, y_train, y_test = train_test_split(dataset, label,
test_size = 0.2, random_state = 1234)
print("Train size is ", X_train.shape)
print("Test size is ", X_test.shape)
```

```
X_train = normalize(X_train, axis=1)
X_test = normalize(X_test, axis=1)
```

```
Train size is  (22046, 150, 150)
Test size is  (5512, 150, 150)
```

```
y_train.shape
```

```
(22046,)
```

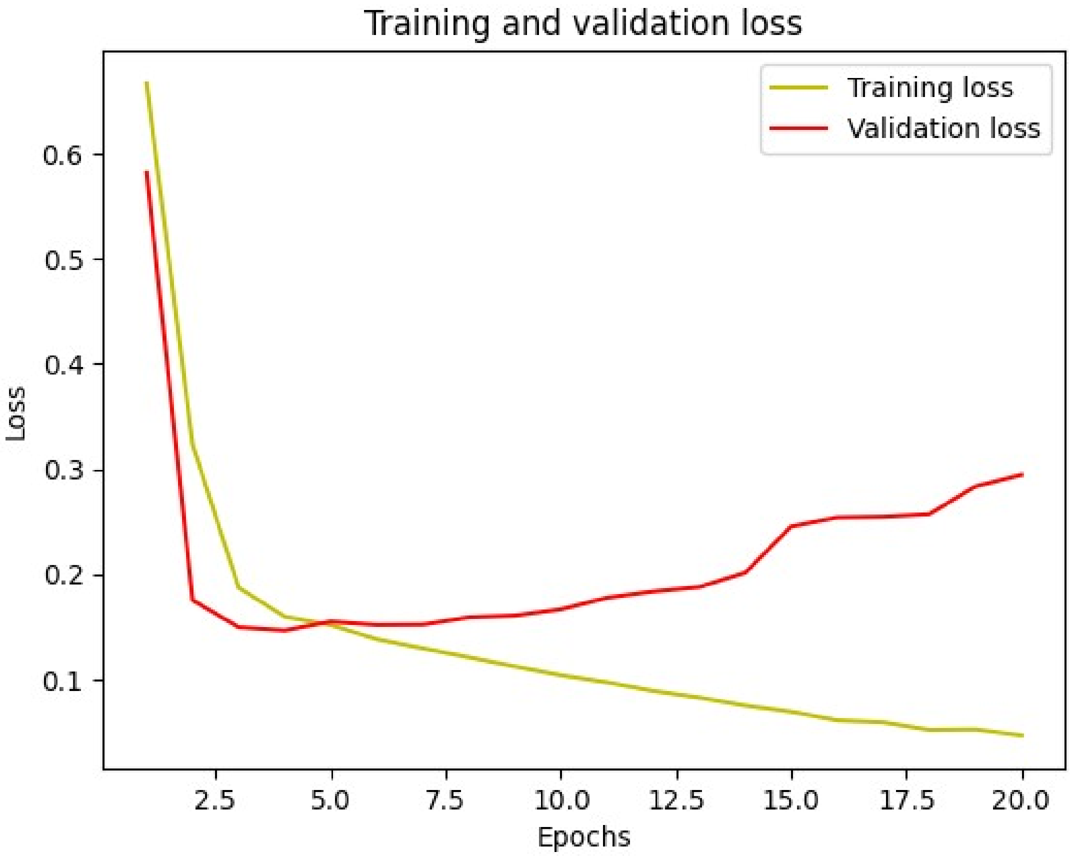
```
input = (img_size, img_size,1)


model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3), input_shape=input,
activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dense(64, activation ='relu'))
model.add(Dropout(0.5))
model.add(Dense(1, activation ='sigmoid'))


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



callback = EarlyStopping(monitor='loss', patience=3)

history = model.fit(X_train, y_train, batch_size = 50,
validation_data=(X_test, y_test), verbose = 1, epochs = 20,
callbacks=[callback])
```

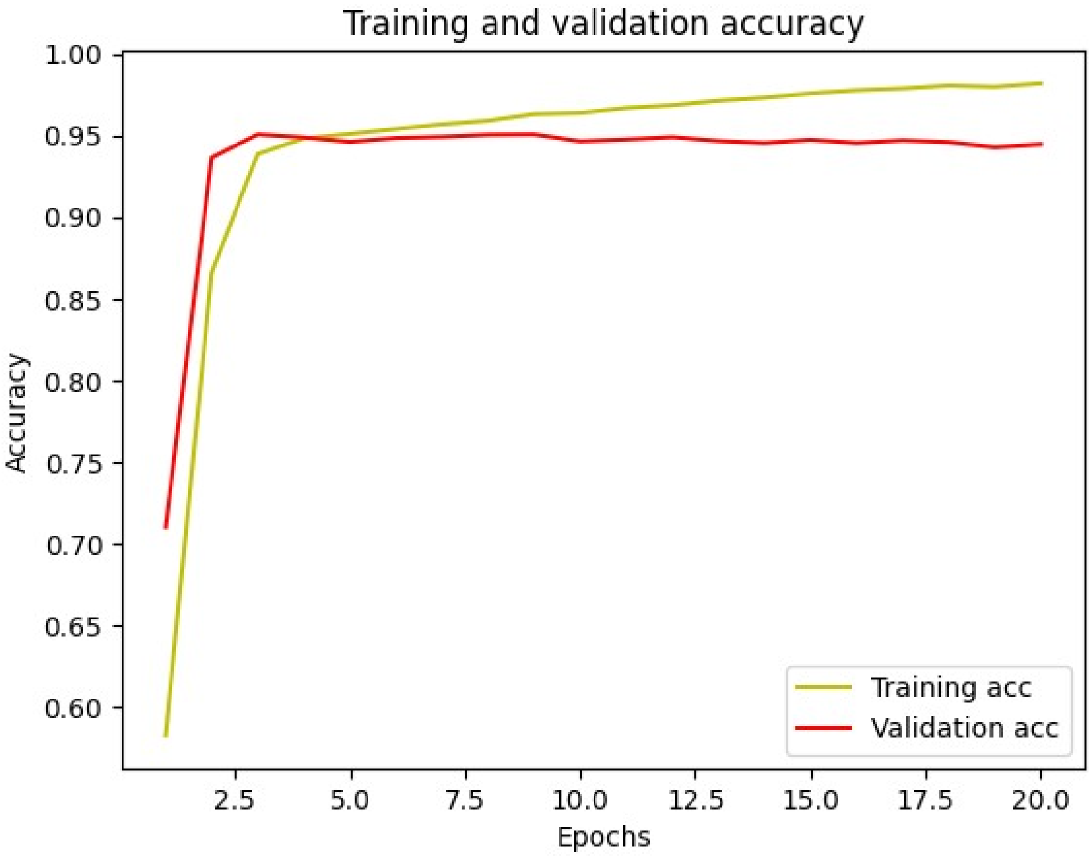
```
Epoch 1/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 62s 133ms/step - accuracy: 0.5528 - loss:
0.6849 - val_accuracy: 0.7103 - val_loss: 0.5823
Epoch 2/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 230s 470ms/step - accuracy: 0.7940 -
loss: 0.4342 - val_accuracy: 0.9365 - val_loss: 0.1751
Epoch 3/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 57s 128ms/step - accuracy: 0.9377 - loss:
0.1908 - val_accuracy: 0.9505 - val_loss: 0.1493
Epoch 4/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 43s 98ms/step - accuracy: 0.9459 - loss:
0.1576 - val_accuracy: 0.9487 - val_loss: 0.1463
```

```
Epoch 5/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 42s 96ms/step - accuracy: 0.9521 - loss: 
0.1452 - val_accuracy: 0.9459 - val_loss: 0.1547
Epoch 6/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 42s 95ms/step - accuracy: 0.9564 - loss: 
0.1347 - val_accuracy: 0.9483 - val_loss: 0.1516
Epoch 7/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 42s 94ms/step - accuracy: 0.9565 - loss: 
0.1313 - val_accuracy: 0.9490 - val_loss: 0.1519
Epoch 8/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 42s 94ms/step - accuracy: 0.9605 - loss: 
0.1155 - val_accuracy: 0.9503 - val_loss: 0.1587
Epoch 9/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 42s 95ms/step - accuracy: 0.9645 - loss: 
0.1115 - val_accuracy: 0.9505 - val_loss: 0.1604
Epoch 10/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 41s 94ms/step - accuracy: 0.9659 - loss: 
0.1008 - val_accuracy: 0.9463 - val_loss: 0.1664
Epoch 11/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 42s 95ms/step - accuracy: 0.9684 - loss: 
0.0952 - val_accuracy: 0.9474 - val_loss: 0.1773
Epoch 12/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 42s 96ms/step - accuracy: 0.9691 - loss: 
0.0841 - val_accuracy: 0.9488 - val_loss: 0.1833
Epoch 13/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 42s 96ms/step - accuracy: 0.9719 - loss: 
0.0806 - val_accuracy: 0.9465 - val_loss: 0.1875
Epoch 14/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 42s 95ms/step - accuracy: 0.9737 - loss: 
0.0727 - val_accuracy: 0.9452 - val_loss: 0.2011
Epoch 15/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 42s 96ms/step - accuracy: 0.9762 - loss: 
0.0687 - val_accuracy: 0.9472 - val_loss: 0.2452
Epoch 16/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 42s 94ms/step - accuracy: 0.9770 - loss: 
0.0638 - val_accuracy: 0.9452 - val_loss: 0.2538
Epoch 17/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 43s 97ms/step - accuracy: 0.9793 - loss: 
0.0570 - val_accuracy: 0.9468 - val_loss: 0.2545
Epoch 18/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 105s 238ms/step - accuracy: 0.9814 - 
loss: 0.0486 - val_accuracy: 0.9458 - val_loss: 0.2570
Epoch 19/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 185s 418ms/step - accuracy: 0.9813 - 
loss: 0.0468 - val_accuracy: 0.9427 - val_loss: 0.2833
Epoch 20/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 102s 232ms/step - accuracy: 0.9814 - 
loss: 0.0473 - val_accuracy: 0.9445 - val_loss: 0.2943

model.summary()
```

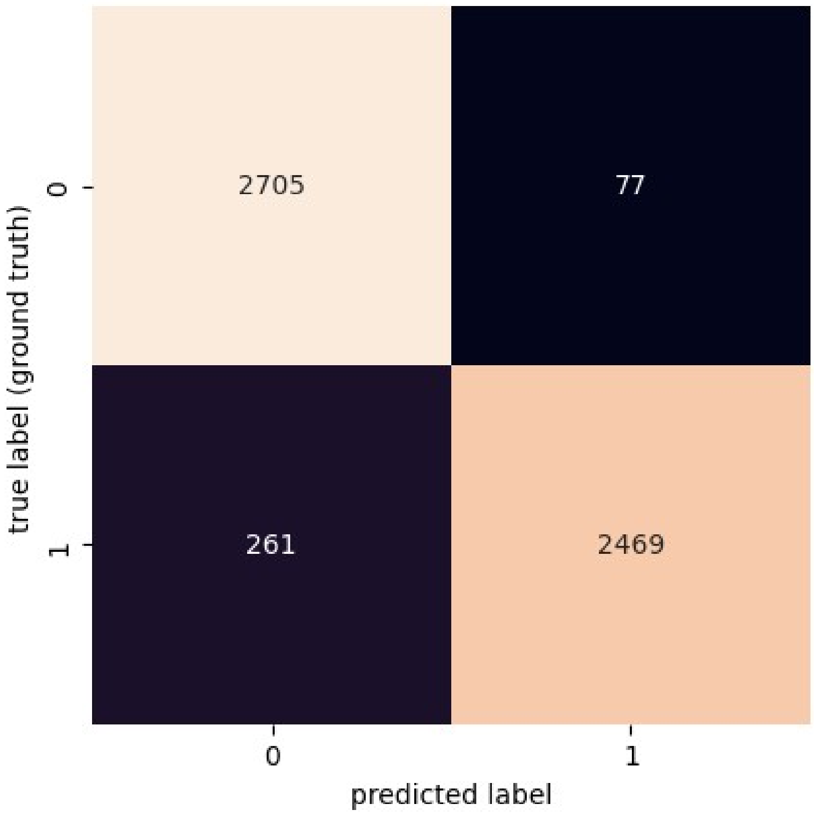
```
Model: "sequential"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━
━━━━━┓
┃ Layer (type)                    ┃ Output Shape           ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━
━━━━━┩
│ conv2d (Conv2D)                 │ (None, 148, 148, 32)   │
320 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ max_pooling2d (MaxPooling2D)    │ (None, 74, 74, 32)     │
0 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ conv2d_1 (Conv2D)               │ (None, 72, 72, 32)     │
9,248 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ max_pooling2d_1 (MaxPooling2D)  │ (None, 36, 36, 32)     │
0 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ conv2d_2 (Conv2D)               │ (None, 34, 34, 64)     │
18,496 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ max_pooling2d_2 (MaxPooling2D)  │ (None, 17, 17, 64)     │
0 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ flatten (Flatten)               │ (None, 18496)          │
0 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dense (Dense)                   │ (None, 64)             │
1,183,808 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dropout (Dropout)               │ (None, 64)             │
0 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dense_1 (Dense)                 │ (None, 1)              │
65 │
└─────────────────────────────────┴────────────────────────┴──────────
─────┘

 Total params: 3,635,813 (13.87 MB)
 Trainable params: 1,211,937 (4.62 MB)

 Non-trainable params: 0 (0.00 B)

 Optimizer params: 2,423,876 (9.25 MB)
```

```python
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()
```

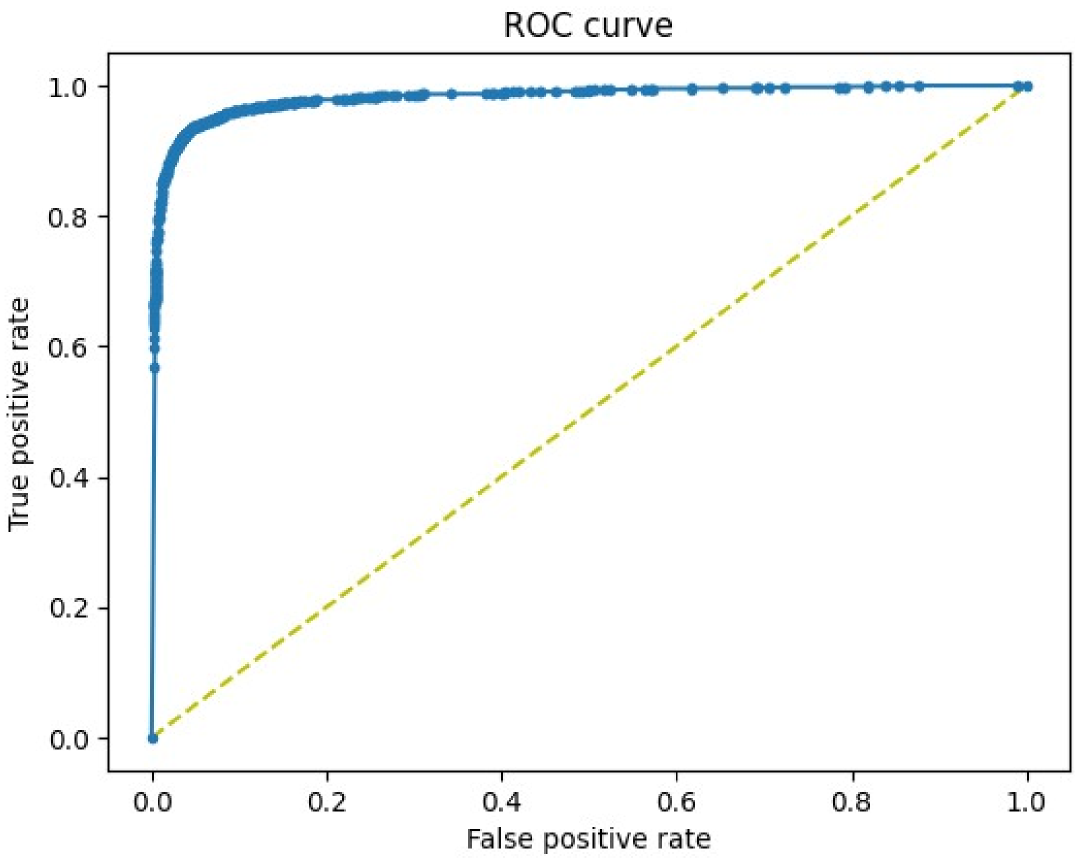

Training and validation loss
Training loss
Validation loss
Loss
0.1
0.2
0.3
0.4
0.5
0.6
Epochs
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0



```
mythreshold=0.785
y_pred_M1=(model.predict(X_test)>= mythreshold).astype(int)
print(classification_report(y_test, y_pred_M1))

173/173 ━━━━━━━━━━━━━━━━━━━━ 3s 19ms/step
              precision    recall  f1-score   support

           0       0.91      0.97      0.94      2782
           1       0.97      0.90      0.94      2730

    accuracy                           0.94      5512
   macro avg       0.94      0.94      0.94      5512
weighted avg       0.94      0.94      0.94      5512


cm=confusion_matrix(y_test, y_pred_M1)
sns.heatmap(cm, square=True, annot=True, fmt='d', cbar=False)
plt.xlabel('predicted label')
plt.ylabel('true label (ground truth)')
plt.show()
```



```
y_preds = model.predict(X_test).ravel()

fpr, tpr, thresholds = roc_curve(y_test, y_preds)
plt.figure(1)
plt.plot([0, 1], [0, 1], 'y--')
plt.plot(fpr, tpr, marker='.')
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title('ROC curve')
plt.show()

173/173 ━━━━━━━━━━━━━━━━━━━━ 3s 18ms/step
```



```
print( 'Precision is : %.2f%%' % (precision_score(y_test, y_pred_M1) *
100))
```

```
Precision is : 96.98%
```

```
print( 'Recall Score is : %.2f%%' % (recall_score(y_test, y_pred_M1) *
100))
```

```
Recall Score is : 90.44%
```

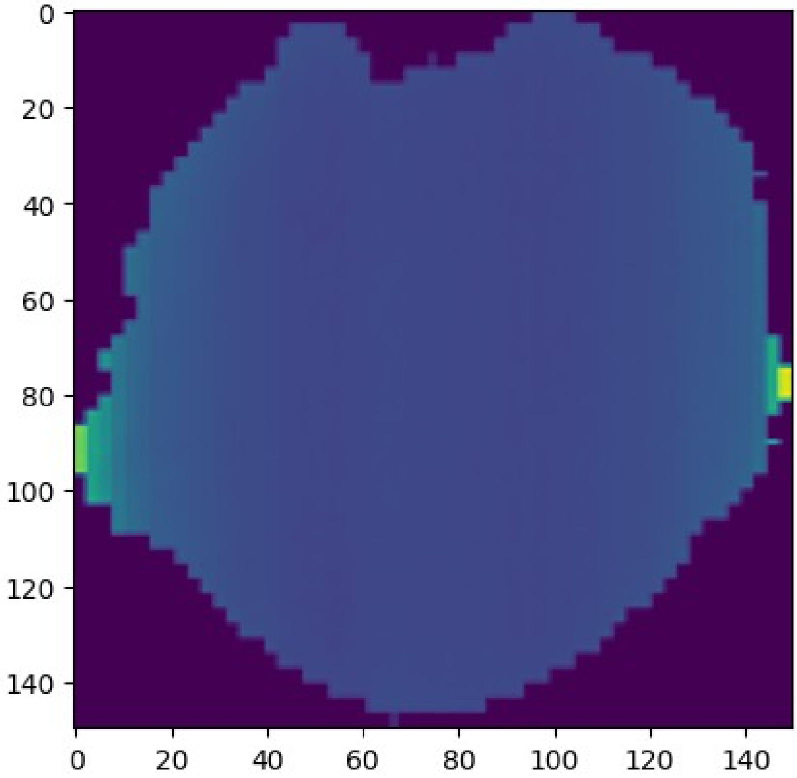
```
print( 'F1 Score is : %.2f%%' % (f1_score(y_test, y_pred_M1) * 100))
```

```
F1 Score is : 93.59%
```

An example of the model classifying the input image.

```
n=588
img = X_test[n]
plt.imshow(img)
input_img = np.expand_dims(img, axis=0)
print("The prediction for this image is: ", model.predict(input_img))
print("The actual label for this image is: ", y_test[n])
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
The prediction for this image is:  [[0.00463257]]
The actual label for this image is:  0
```

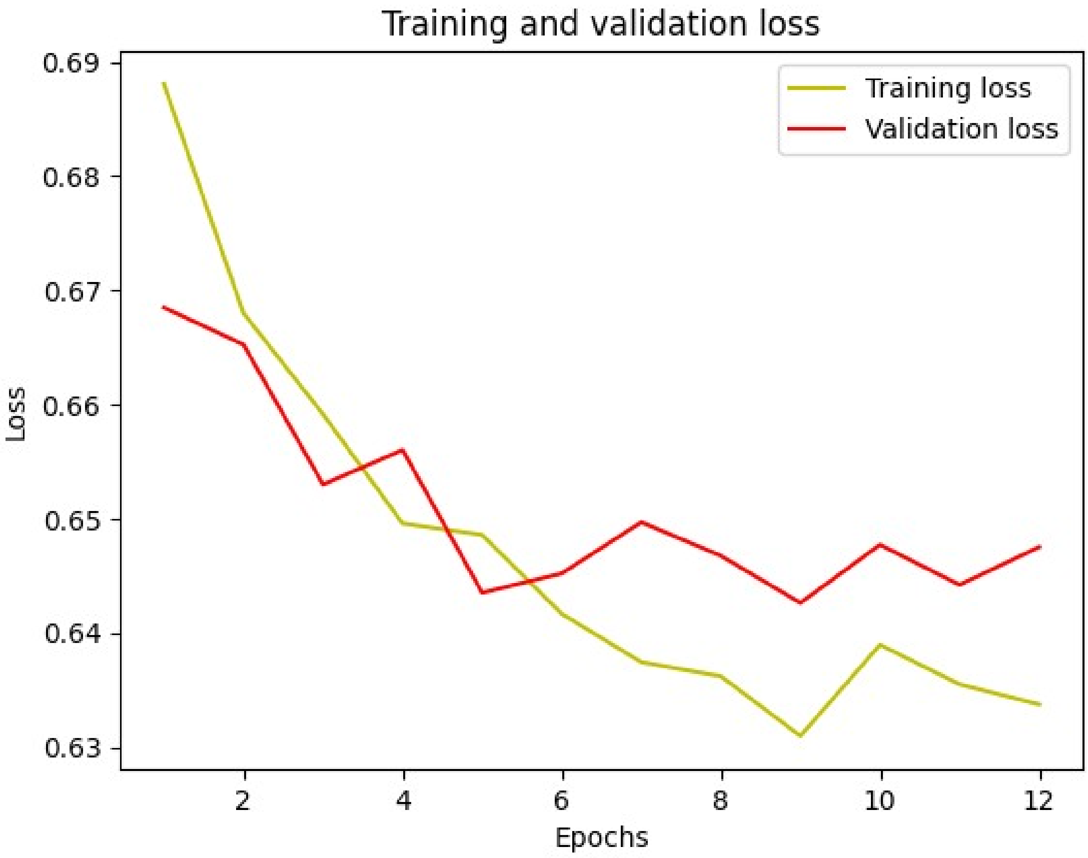


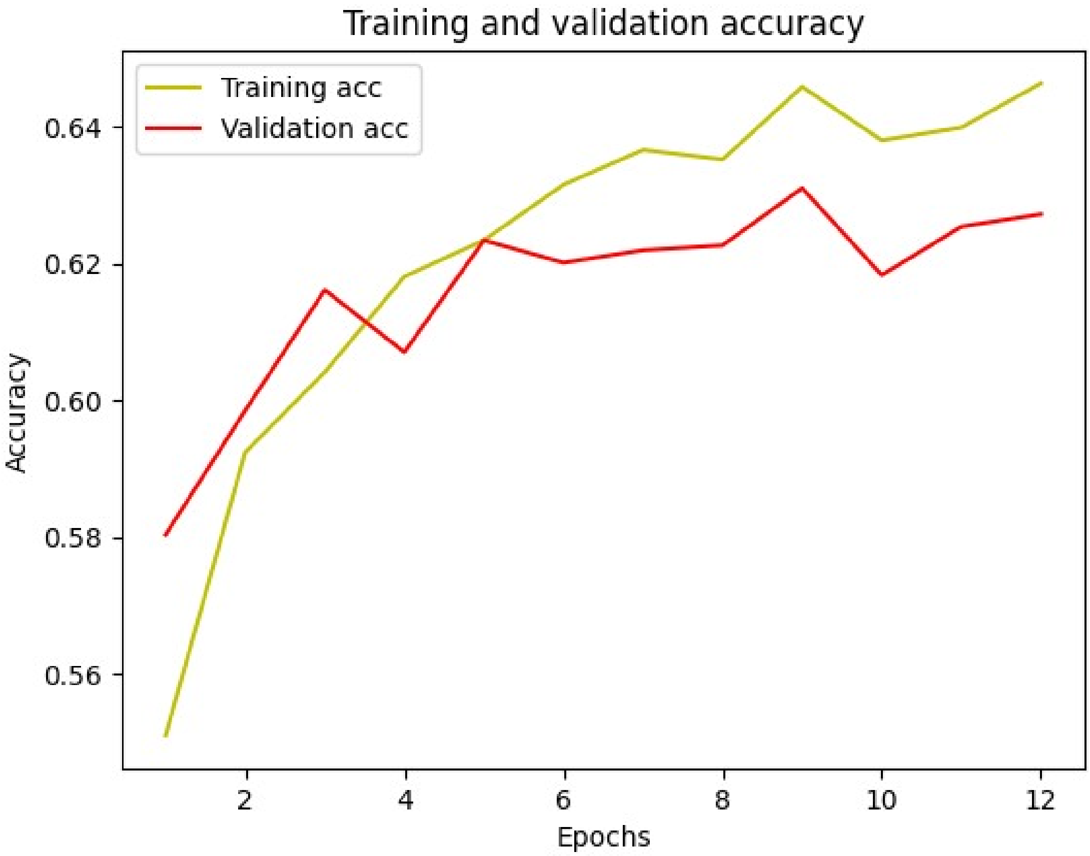
ANN MODEL

```
from keras.layers import Input
from keras.optimizers import Adam
model2 =  Sequential([

    Input(shape=(img_size, img_size,1)),


    Flatten(),


    Dense(512, activation='relu'),
    Dense(256, activation='relu'),
    Dense(128, activation='relu'),
    Dense(64, activation='relu'),
    Dense(32, activation='relu'),
    Dense(16, activation='relu'),


    Dense(1, activation='sigmoid')
])

model2.summary()

Model: "sequential_4"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━
━━━━━┓
┃ Layer (type)                    ┃ Output Shape           ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━
━━━━━┩
│ flatten_4 (Flatten)             │ (None, 22500)          │
0 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dense_18 (Dense)                │ (None, 512)            │
11,520,512 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dense_19 (Dense)                │ (None, 256)            │
131,328 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dense_20 (Dense)                │ (None, 128)            │
32,896 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dense_21 (Dense)                │ (None, 64)             │
8,256 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dense_22 (Dense)                │ (None, 32)             │
2,080 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dense_23 (Dense)                │ (None, 16)             │
528 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dense_24 (Dense)                │ (None, 1)              │
17 │
└─────────────────────────────────┴────────────────────────┴──────────
─────┘

 Total params: 11,695,617 (44.62 MB)

 Trainable params: 11,695,617 (44.62 MB)

 Non-trainable params: 0 (0.00 B)
```

```
model2.compile(loss='binary_crossentropy', optimizer='adam',
metrics=['accuracy'])



callback = EarlyStopping(monitor='loss', patience=3)

history = model2.fit(X_train, y_train, batch_size = 50,
validation_data=(X_test, y_test), verbose = 1, epochs = 20,
callbacks=[callback])

Epoch 1/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 25s 48ms/step - accuracy: 0.5321 - loss:
0.7030 - val_accuracy: 0.5804 - val_loss: 0.6685
Epoch 2/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 17s 40ms/step - accuracy: 0.5860 - loss:
0.6683 - val_accuracy: 0.5985 - val_loss: 0.6652
Epoch 3/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 17s 39ms/step - accuracy: 0.5922 - loss:
0.6624 - val_accuracy: 0.6161 - val_loss: 0.6530
Epoch 4/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 17s 39ms/step - accuracy: 0.6166 - loss:
0.6509 - val_accuracy: 0.6070 - val_loss: 0.6560
Epoch 5/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 17s 38ms/step - accuracy: 0.6185 - loss:
0.6500 - val_accuracy: 0.6234 - val_loss: 0.6435
Epoch 6/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 17s 39ms/step - accuracy: 0.6353 - loss:
0.6397 - val_accuracy: 0.6201 - val_loss: 0.6452
Epoch 7/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 17s 39ms/step - accuracy: 0.6371 - loss:
0.6377 - val_accuracy: 0.6219 - val_loss: 0.6497
Epoch 8/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 17s 38ms/step - accuracy: 0.6333 - loss:
0.6380 - val_accuracy: 0.6226 - val_loss: 0.6467
Epoch 9/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 17s 39ms/step - accuracy: 0.6457 - loss:
0.6309 - val_accuracy: 0.6310 - val_loss: 0.6426
Epoch 10/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 17s 39ms/step - accuracy: 0.6404 - loss:
0.6330 - val_accuracy: 0.6183 - val_loss: 0.6477
Epoch 11/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 17s 39ms/step - accuracy: 0.6391 - loss:
0.6354 - val_accuracy: 0.6254 - val_loss: 0.6442
Epoch 12/20
441/441 ━━━━━━━━━━━━━━━━━━━━ 17s 39ms/step - accuracy: 0.6377 - loss:
0.6383 - val_accuracy: 0.6272 - val_loss: 0.6475


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()
```





```
mythreshold=0.785
y_pred_M1=(model2.predict(X_test)>= mythreshold).astype(int)
print(classification_report(y_test, y_pred_M1))

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              precision    recall  f1-score   support

           0       0.50      1.00      0.67      2782
           1       0.00      0.00      0.00      2730

    accuracy                           0.50      5512
   macro avg       0.25      0.50      0.34      5512
weighted avg       0.25      0.50      0.34      5512
```