melanoma-skin-cancer

April 27, 2023

Importing the data from Kaggle

[1]:
```
! pip install -q kaggle
from google.colab import files
files.upload()
! mkdir ~/.kaggle
! cp kaggle.json ~/.kaggle/
! chmod 600 ~/.kaggle/kaggle.json
```

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

```
Saving kaggle.json to kaggle (2).json
mkdir: cannot create directory '/root/.kaggle': File exists
```

[2]:
```
!kaggle datasets download -d hasnainjaved/
 ↪melanoma-skin-cancer-dataset-of-10000-images
```

```
melanoma-skin-cancer-dataset-of-10000-images.zip: Skipping, found more recently
modified local copy (use --force to force download)
```

[ ]:
```
!unzip melanoma-skin-cancer-dataset-of-10000-images.zip
```

Importing the Dependencies

[4]:
```
import os
import numpy as np
import cv2 as cv
from sklearn.preprocessing import LabelEncoder
from keras.layers import Conv2D, MaxPool2D, Flatten, GlobalAveragePooling2D,␣
 ↪Dense, Dropout, BatchNormalization
from keras.models import Sequential
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from keras.applications.vgg16 import VGG16
import seaborn as sns
import xgboost as xgb
from sklearn.metrics import confusion_matrix, classification_report,␣
 ↪accuracy_score
```

[5]:
```
def input_data(folder_path, output_data):    #importing the data into the␣
 ↪output_data list
  for dirs in os.listdir(folder_path):
    class_name = dirs
    new_path = os.path.join(folder_path, class_name)
    for img in os.listdir(new_path):
      img_arr = cv.imread(os.path.join(new_path, img), cv.IMREAD_GRAYSCALE)
      resize = cv.resize(img_arr, (128,128))
      output_data.append([resize, class_name])
  return output_data
```

[6]:
```
train_data = input_data("/content/melanoma_cancer_dataset/train", [])
test_data = input_data("/content/melanoma_cancer_dataset/test", [])
```

[7]:
```
np.random.shuffle(train_data)   #shuffling the data
np.random.shuffle(test_data)
```

[8]:
```
train_images = []             #separating the image and labels from the␣
 ↪train_data list
train_labels = []
for features, labels in train_data:
  train_images.append(features)
  train_labels.append(labels)
```

[9]:
```
test_images = []    #separating the image and labels from the test_data list
test_labels = []
for features, labels in test_data:
  test_images.append(features)
  test_labels.append(labels)
```

[10]:
```
label_enc = LabelEncoder()           # encoding the labels
train_labels = label_enc.fit_transform(train_labels)
test_labels = label_enc.transform(test_labels)
```

[11]:
```
train_images = np.array(train_images)    #converting the images and labels into␣
 ↪numpy array
train_labels = np.array(train_labels)
test_images = np.array(test_images)
test_labels = np.array(test_labels)
```

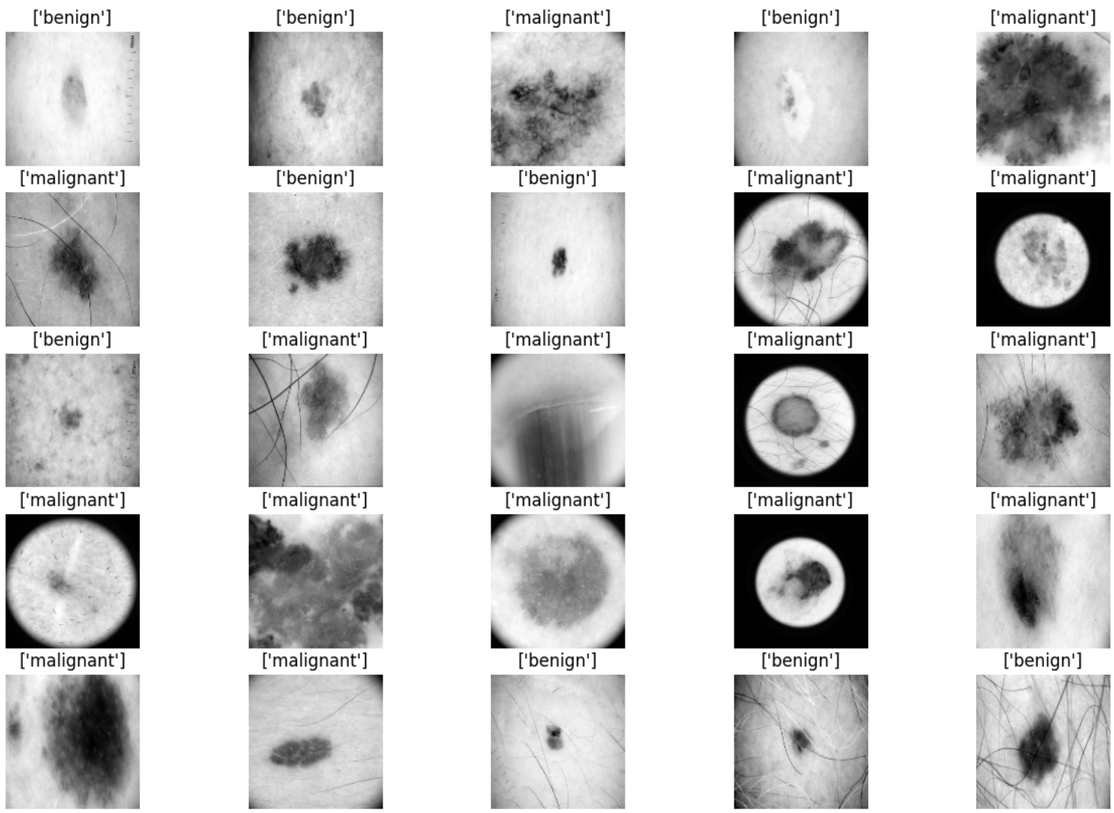
[12]:
```
train_images = train_images/255    # normalizing the image pixels
test_images = test_images/255
```

[13]:
```
train_images = np.expand_dims(train_images, axis=3)      # adding a dimension␣
 ↪on the images
test_images = np.expand_dims(test_images, axis=3)
```

[14]:
```
print(f"Shape of the train images {train_images.shape}")
print(f"Shape of the train labels {train_labels.shape}")
print(f"Shape of the test images {test_images.shape}")
print(f"Shape of the test labels {test_labels.shape}")
```

```
Shape of the train images (9605, 128, 128, 1)
Shape of the train labels (9605,)
Shape of the test images (1000, 128, 128, 1)
Shape of the test labels (1000,)
```

[15]:
```
plt.figure(figsize=(15,10))
for i in range(25):
  plt.subplot(5, 5, i+1)
  plt.imshow(test_images[i], cmap='gray')
  plt.title(f"{label_enc.inverse_transform([test_labels[i]])}")
  plt.axis("off")
```



CNN Model

[16]:
```
model1 = Sequential()

model1.add(Conv2D(32, (3, 3), input_shape=(128,128,1), activation="leaky_relu"))
```

```python
model1.add(MaxPool2D(2,2))
model1.add(Conv2D(64, (3, 3), activation="leaky_relu"))
model1.add(MaxPool2D(2,2))
model1.add(Conv2D(128, (3, 3), activation="leaky_relu"))
model1.add(MaxPool2D(2,2))
model1.add(Conv2D(256, (3, 3), activation="leaky_relu"))
model1.add(MaxPool2D(2,2))
model1.add(Flatten())
model1.add(Dense(256, activation="relu"))
model1.add(Dense(1, activation="sigmoid"))
```

[17]:

```python
model1.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 126, 126, 32)      320

 max_pooling2d (MaxPooling2D  (None, 63, 63, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 61, 61, 64)        18496

 max_pooling2d_1 (MaxPooling  (None, 30, 30, 64)       0
 2D)

 conv2d_2 (Conv2D)           (None, 28, 28, 128)       73856

 max_pooling2d_2 (MaxPooling  (None, 14, 14, 128)      0
 2D)

 conv2d_3 (Conv2D)           (None, 12, 12, 256)       295168

 max_pooling2d_3 (MaxPooling  (None, 6, 6, 256)        0
 2D)

 flatten (Flatten)           (None, 9216)              0

 dense (Dense)               (None, 256)               2359552

 dense_1 (Dense)             (None, 1)                 257

=================================================================
Total params: 2,747,649
Trainable params: 2,747,649
Non-trainable params: 0
```

----

[18]:
```
model1.compile(optimizer="adam", loss="binary_crossentropy", metrics =␣
↪['accuracy'])
```

[19]:
```
history1 = model1.fit(train_images, train_labels, validation_data=(test_images,␣
↪test_labels), epochs=30)
```

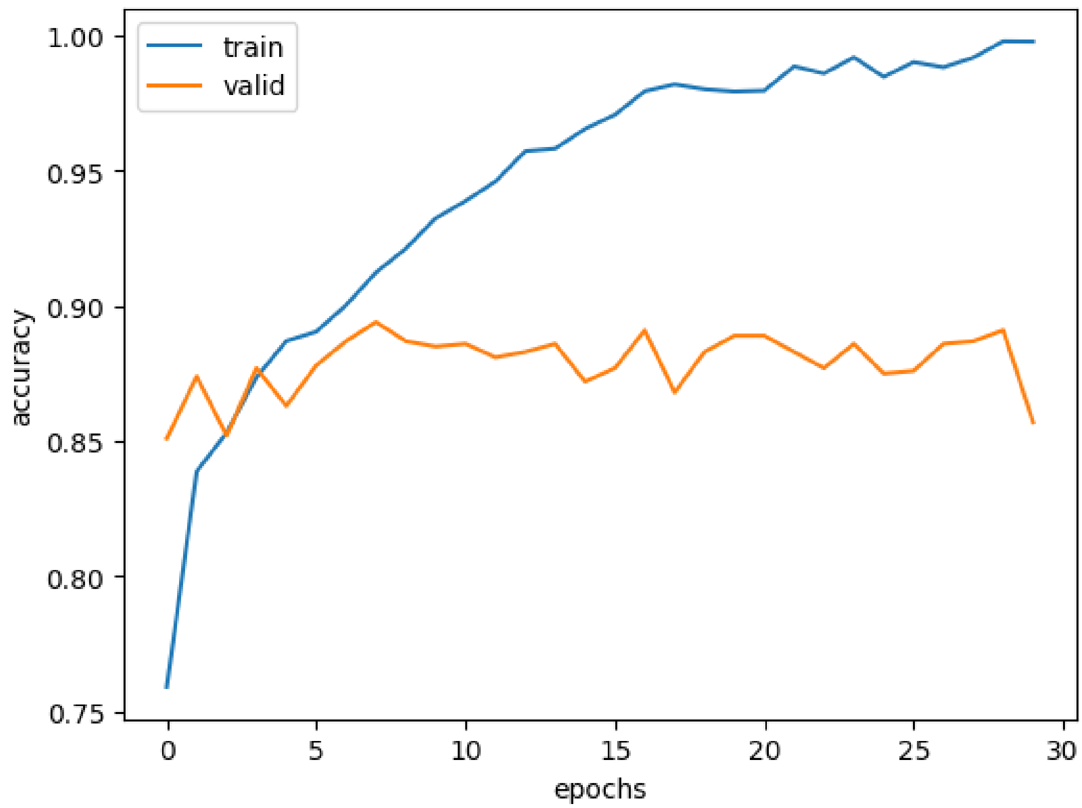
```
Epoch 1/30
301/301 [==============================] - 19s 22ms/step - loss: 0.4563 -
accuracy: 0.7592 - val_loss: 0.3161 - val_accuracy: 0.8510
Epoch 2/30
301/301 [==============================] - 6s 20ms/step - loss: 0.3372 -
accuracy: 0.8388 - val_loss: 0.2835 - val_accuracy: 0.8740
Epoch 3/30
301/301 [==============================] - 6s 20ms/step - loss: 0.3141 -
accuracy: 0.8531 - val_loss: 0.3062 - val_accuracy: 0.8520
Epoch 4/30
301/301 [==============================] - 6s 20ms/step - loss: 0.2848 -
accuracy: 0.8736 - val_loss: 0.2739 - val_accuracy: 0.8770
Epoch 5/30
301/301 [==============================] - 6s 20ms/step - loss: 0.2622 -
accuracy: 0.8870 - val_loss: 0.3190 - val_accuracy: 0.8630
Epoch 6/30
301/301 [==============================] - 6s 20ms/step - loss: 0.2553 -
accuracy: 0.8905 - val_loss: 0.2891 - val_accuracy: 0.8780
Epoch 7/30
301/301 [==============================] - 6s 20ms/step - loss: 0.2331 -
accuracy: 0.9003 - val_loss: 0.2909 - val_accuracy: 0.8870
Epoch 8/30
301/301 [==============================] - 6s 21ms/step - loss: 0.2155 -
accuracy: 0.9123 - val_loss: 0.2814 - val_accuracy: 0.8940
Epoch 9/30
301/301 [==============================] - 6s 20ms/step - loss: 0.1968 -
accuracy: 0.9212 - val_loss: 0.3066 - val_accuracy: 0.8870
Epoch 10/30
301/301 [==============================] - 6s 20ms/step - loss: 0.1746 -
accuracy: 0.9324 - val_loss: 0.2976 - val_accuracy: 0.8850
Epoch 11/30
301/301 [==============================] - 6s 20ms/step - loss: 0.1577 -
accuracy: 0.9388 - val_loss: 0.3640 - val_accuracy: 0.8860
Epoch 12/30
301/301 [==============================] - 6s 21ms/step - loss: 0.1386 -
accuracy: 0.9460 - val_loss: 0.3979 - val_accuracy: 0.8810
Epoch 13/30
301/301 [==============================] - 6s 20ms/step - loss: 0.1152 -
accuracy: 0.9572 - val_loss: 0.4101 - val_accuracy: 0.8830
Epoch 14/30
```

```
301/301 [==============================] - 6s 20ms/step - loss: 0.1073 -
accuracy: 0.9581 - val_loss: 0.4877 - val_accuracy: 0.8860
Epoch 15/30
301/301 [==============================] - 6s 20ms/step - loss: 0.0898 -
accuracy: 0.9654 - val_loss: 0.5005 - val_accuracy: 0.8720
Epoch 16/30
301/301 [==============================] - 6s 20ms/step - loss: 0.0853 -
accuracy: 0.9706 - val_loss: 0.5980 - val_accuracy: 0.8770
Epoch 17/30
301/301 [==============================] - 6s 20ms/step - loss: 0.0584 -
accuracy: 0.9794 - val_loss: 0.6521 - val_accuracy: 0.8910
Epoch 18/30
301/301 [==============================] - 6s 20ms/step - loss: 0.0529 -
accuracy: 0.9819 - val_loss: 0.6774 - val_accuracy: 0.8680
Epoch 19/30
301/301 [==============================] - 6s 20ms/step - loss: 0.0528 -
accuracy: 0.9801 - val_loss: 0.8797 - val_accuracy: 0.8830
Epoch 20/30
301/301 [==============================] - 6s 20ms/step - loss: 0.0571 -
accuracy: 0.9793 - val_loss: 0.6925 - val_accuracy: 0.8890
Epoch 21/30
301/301 [==============================] - 6s 21ms/step - loss: 0.0603 -
accuracy: 0.9796 - val_loss: 0.7770 - val_accuracy: 0.8890
Epoch 22/30
301/301 [==============================] - 6s 21ms/step - loss: 0.0306 -
accuracy: 0.9885 - val_loss: 0.8078 - val_accuracy: 0.8830
Epoch 23/30
301/301 [==============================] - 6s 21ms/step - loss: 0.0458 -
accuracy: 0.9859 - val_loss: 0.7029 - val_accuracy: 0.8770
Epoch 24/30
301/301 [==============================] - 6s 21ms/step - loss: 0.0236 -
accuracy: 0.9919 - val_loss: 0.9889 - val_accuracy: 0.8860
Epoch 25/30
301/301 [==============================] - 6s 21ms/step - loss: 0.0486 -
accuracy: 0.9847 - val_loss: 0.8635 - val_accuracy: 0.8750
Epoch 26/30
301/301 [==============================] - 6s 21ms/step - loss: 0.0348 -
accuracy: 0.9901 - val_loss: 0.9185 - val_accuracy: 0.8760
Epoch 27/30
301/301 [==============================] - 6s 21ms/step - loss: 0.0338 -
accuracy: 0.9882 - val_loss: 1.0175 - val_accuracy: 0.8860
Epoch 28/30
301/301 [==============================] - 6s 21ms/step - loss: 0.0262 -
accuracy: 0.9918 - val_loss: 1.0017 - val_accuracy: 0.8870
Epoch 29/30
301/301 [==============================] - 6s 20ms/step - loss: 0.0075 -
accuracy: 0.9978 - val_loss: 1.2161 - val_accuracy: 0.8910
Epoch 30/30
```

```
301/301 [==============================] - 6s 20ms/step - loss: 0.0074 -
accuracy: 0.9977 - val_loss: 1.4788 - val_accuracy: 0.8570
```

[20]:

```
plt.plot(history1.history["accuracy"])
plt.plot(history1.history["val_accuracy"])
plt.xlabel("epochs")
plt.ylabel("accuracy")
plt.legend(["train","valid"])
plt.show()
```



[21]:

```
y_pred1 = model1.predict(test_images)
```

```
32/32 [==============================] - 0s 8ms/step
```

[22]:

```
y_pred1 = np.where(y_pred1>0.6,1,0)
```

[23]:

```
y_pred1 = y_pred1.reshape(1,-1)[0]
```

[24]:

```
print(classification_report(y_pred1, test_labels))
```

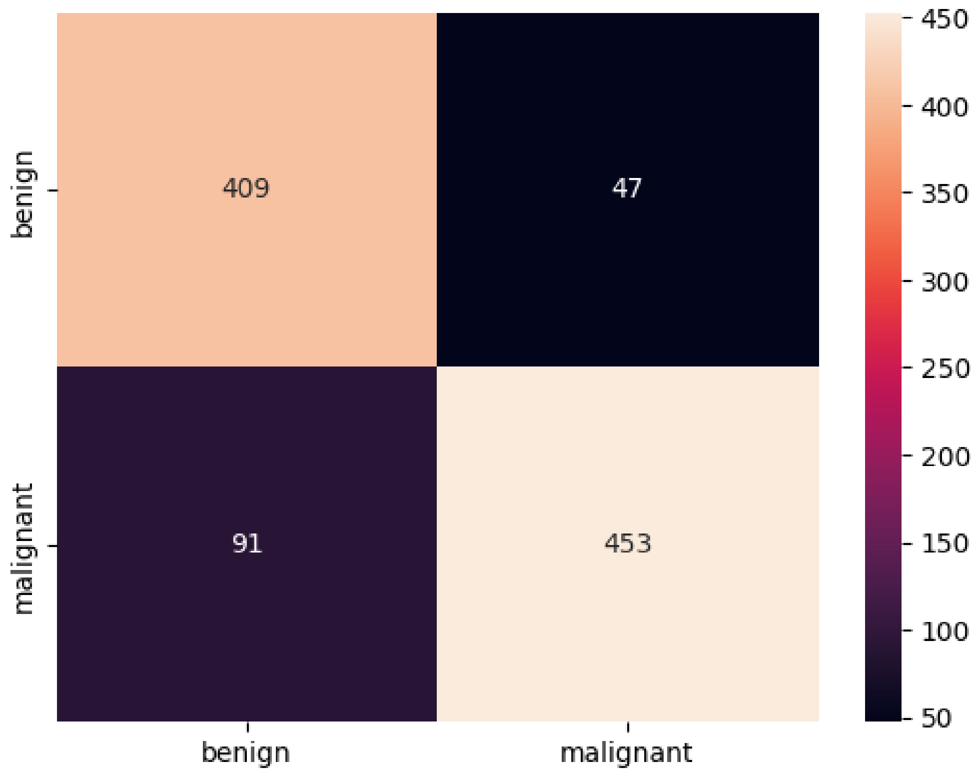
```
              precision    recall  f1-score   support
```

```
              0       0.82      0.90      0.86       456
              1       0.91      0.83      0.87       544

       accuracy                           0.86      1000
      macro avg       0.86      0.86      0.86      1000
   weighted avg       0.87      0.86      0.86      1000
```

[25]:
```
sns.heatmap(confusion_matrix(y_pred1, test_labels), fmt='g', annot=True ,␣
↪xticklabels=["benign", "malignant"], yticklabels=["benign", "malignant"])
```

[25]:
```
<Axes: >
```



CNN Model with Dropout and GAP Layer

[26]:
```
model2 = Sequential()

model2.add(Conv2D(32, (3,3), input_shape=(128,128,1), activation="leaky_relu"))
model2.add(Dropout(0.1))
model2.add(MaxPool2D(2,2))
model2.add(Conv2D(64, (3,3), activation="leaky_relu"))
model2.add(Dropout(0.2))
```

```
model2.add(MaxPool2D(2,2))
model2.add(Conv2D(128, (3,3), activation="leaky_relu"))
model2.add(Dropout(0.3))
model2.add(MaxPool2D(2,2))
model2.add(GlobalAveragePooling2D())
model2.add(Dense(128, activation="leaky_relu"))
model2.add(Dense(1, activation="sigmoid"))
```

[27]:
```
model2.compile(optimizer='adam', loss='binary_crossentropy',␣
↪metrics=['accuracy'])
```

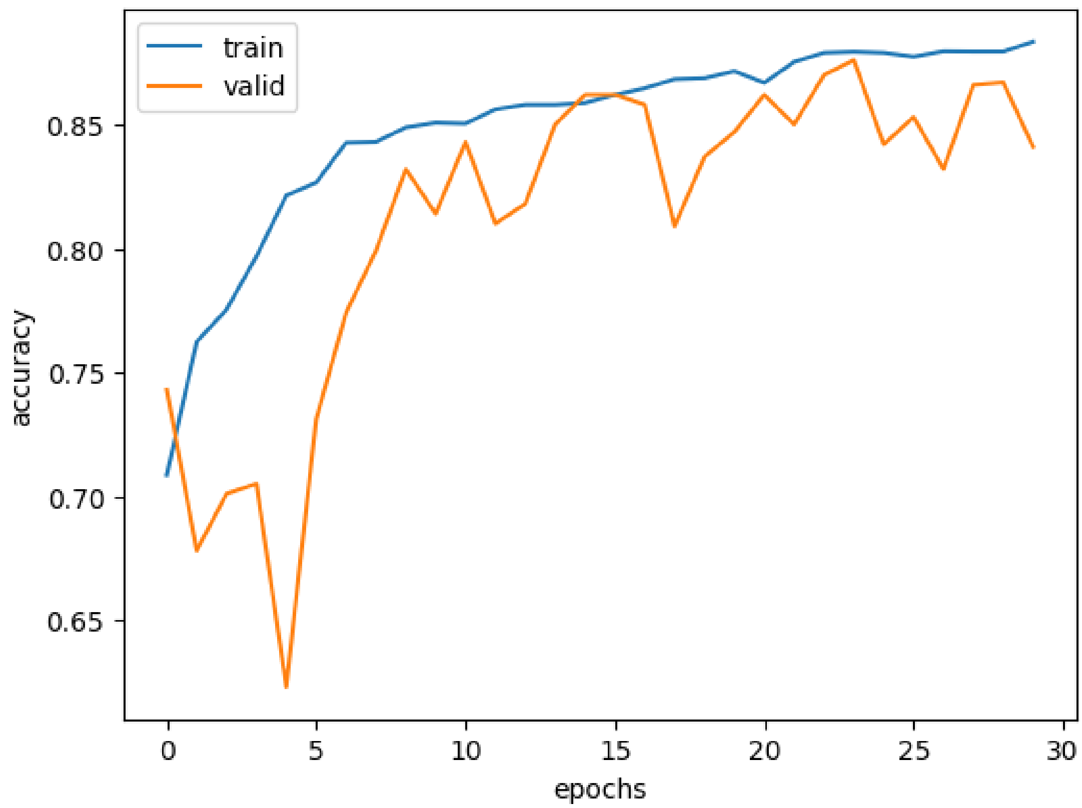
[28]:
```
history2 = model2.fit(train_images, train_labels, validation_data=(test_images,␣
↪test_labels), batch_size=28, epochs=30)
```

```
Epoch 1/30
344/344 [==============================] - 13s 31ms/step - loss: 0.5289 -
accuracy: 0.7085 - val_loss: 0.5978 - val_accuracy: 0.7430
Epoch 2/30
344/344 [==============================] - 10s 29ms/step - loss: 0.4594 -
accuracy: 0.7623 - val_loss: 0.6232 - val_accuracy: 0.6780
Epoch 3/30
344/344 [==============================] - 10s 28ms/step - loss: 0.4378 -
accuracy: 0.7753 - val_loss: 0.6603 - val_accuracy: 0.7010
Epoch 4/30
344/344 [==============================] - 10s 29ms/step - loss: 0.4083 -
accuracy: 0.7968 - val_loss: 0.6189 - val_accuracy: 0.7050
Epoch 5/30
344/344 [==============================] - 10s 29ms/step - loss: 0.3750 -
accuracy: 0.8213 - val_loss: 0.9924 - val_accuracy: 0.6230
Epoch 6/30
344/344 [==============================] - 10s 29ms/step - loss: 0.3705 -
accuracy: 0.8265 - val_loss: 0.6504 - val_accuracy: 0.7310
Epoch 7/30
344/344 [==============================] - 10s 28ms/step - loss: 0.3505 -
accuracy: 0.8427 - val_loss: 0.6242 - val_accuracy: 0.7740
Epoch 8/30
344/344 [==============================] - 10s 29ms/step - loss: 0.3434 -
accuracy: 0.8430 - val_loss: 0.4935 - val_accuracy: 0.7990
Epoch 9/30
344/344 [==============================] - 10s 28ms/step - loss: 0.3395 -
accuracy: 0.8488 - val_loss: 0.3838 - val_accuracy: 0.8320
Epoch 10/30
344/344 [==============================] - 10s 28ms/step - loss: 0.3366 -
accuracy: 0.8507 - val_loss: 0.5389 - val_accuracy: 0.8140
Epoch 11/30
344/344 [==============================] - 10s 28ms/step - loss: 0.3333 -
accuracy: 0.8504 - val_loss: 0.3679 - val_accuracy: 0.8430
```

```
Epoch 12/30
344/344 [==============================] - 10s 28ms/step - loss: 0.3262 -
accuracy: 0.8561 - val_loss: 0.5070 - val_accuracy: 0.8100
Epoch 13/30
344/344 [==============================] - 10s 28ms/step - loss: 0.3240 -
accuracy: 0.8580 - val_loss: 0.5802 - val_accuracy: 0.8180
Epoch 14/30
344/344 [==============================] - 10s 28ms/step - loss: 0.3208 -
accuracy: 0.8580 - val_loss: 0.3894 - val_accuracy: 0.8500
Epoch 15/30
344/344 [==============================] - 10s 28ms/step - loss: 0.3149 -
accuracy: 0.8587 - val_loss: 0.3447 - val_accuracy: 0.8620
Epoch 16/30
344/344 [==============================] - 10s 28ms/step - loss: 0.3060 -
accuracy: 0.8619 - val_loss: 0.3393 - val_accuracy: 0.8620
Epoch 17/30
344/344 [==============================] - 10s 28ms/step - loss: 0.3074 -
accuracy: 0.8647 - val_loss: 0.3778 - val_accuracy: 0.8580
Epoch 18/30
344/344 [==============================] - 9s 28ms/step - loss: 0.3024 -
accuracy: 0.8683 - val_loss: 0.3722 - val_accuracy: 0.8090
Epoch 19/30
344/344 [==============================] - 10s 28ms/step - loss: 0.2971 -
accuracy: 0.8687 - val_loss: 0.5652 - val_accuracy: 0.8370
Epoch 20/30
344/344 [==============================] - 10s 28ms/step - loss: 0.2930 -
accuracy: 0.8715 - val_loss: 0.3476 - val_accuracy: 0.8470
Epoch 21/30
344/344 [==============================] - 10s 28ms/step - loss: 0.2986 -
accuracy: 0.8668 - val_loss: 0.3217 - val_accuracy: 0.8620
Epoch 22/30
344/344 [==============================] - 10s 28ms/step - loss: 0.2890 -
accuracy: 0.8753 - val_loss: 0.3442 - val_accuracy: 0.8500
Epoch 23/30
344/344 [==============================] - 10s 28ms/step - loss: 0.2847 -
accuracy: 0.8789 - val_loss: 0.3481 - val_accuracy: 0.8700
Epoch 24/30
344/344 [==============================] - 10s 28ms/step - loss: 0.2807 -
accuracy: 0.8793 - val_loss: 0.3166 - val_accuracy: 0.8760
Epoch 25/30
344/344 [==============================] - 10s 28ms/step - loss: 0.2799 -
accuracy: 0.8789 - val_loss: 0.3869 - val_accuracy: 0.8420
Epoch 26/30
344/344 [==============================] - 10s 28ms/step - loss: 0.2823 -
accuracy: 0.8774 - val_loss: 0.4026 - val_accuracy: 0.8530
Epoch 27/30
344/344 [==============================] - 9s 27ms/step - loss: 0.2768 -
accuracy: 0.8795 - val_loss: 0.4331 - val_accuracy: 0.8320
```

```
Epoch 28/30
344/344 [==============================] - 10s 28ms/step - loss: 0.2773 -
accuracy: 0.8794 - val_loss: 0.3221 - val_accuracy: 0.8660
Epoch 29/30
344/344 [==============================] - 10s 28ms/step - loss: 0.2791 -
accuracy: 0.8794 - val_loss: 0.3164 - val_accuracy: 0.8670
Epoch 30/30
344/344 [==============================] - 10s 28ms/step - loss: 0.2733 -
accuracy: 0.8834 - val_loss: 0.3912 - val_accuracy: 0.8410
```

[29]:
```
plt.plot(history2.history["accuracy"])
plt.plot(history2.history["val_accuracy"])
plt.xlabel("epochs")
plt.ylabel("accuracy")
plt.legend(["train","valid"])
plt.show()
```



[30]:
```
y_pred2 = model2.predict(test_images)
```

```
32/32 [==============================] - 0s 7ms/step
```

[31]:
```python
y_pred2 = np.where(y_pred2>0.6,1,0)
```

[32]:
```python
y_pred2 = y_pred2.reshape(1,-1)[0]
```

[33]:
```python
print(classification_report(y_pred2, test_labels))
```

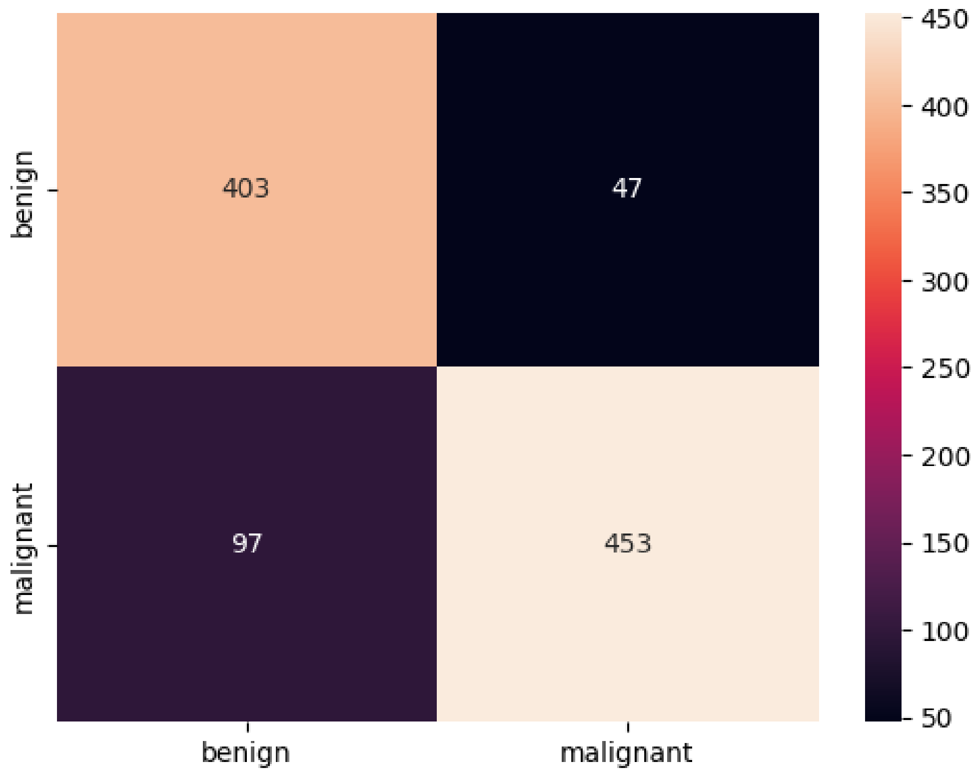
```
              precision    recall  f1-score   support

           0       0.81      0.90      0.85       450
           1       0.91      0.82      0.86       550

    accuracy                           0.86      1000
   macro avg       0.86      0.86      0.86      1000
weighted avg       0.86      0.86      0.86      1000
```

[34]:
```python
sns.heatmap(confusion_matrix(y_pred2, test_labels), fmt='g', annot=True ,␣
↪xticklabels=["benign", "malignant"], yticklabels=["benign", "malignant"])
```

[34]: <Axes: >



CNN Model GAP and BatchNormlization Layer

[35]:
```python
model3 = Sequential()

model3.add(Conv2D(32, (3,3), input_shape=(128,128,1), activation="relu"))
model3.add(BatchNormalization())
model3.add(MaxPool2D(2,2))
model3.add(Conv2D(64, (3,3), activation="relu"))
model3.add(BatchNormalization())
model3.add(MaxPool2D(2,2))
model3.add(Conv2D(128, (3,3), activation="relu"))
model3.add(BatchNormalization())
model3.add(MaxPool2D(2,2))
model3.add(Conv2D(256, (3,3), activation="relu"))
model3.add(BatchNormalization())
model3.add(MaxPool2D(2,2))
model3.add(GlobalAveragePooling2D())
model3.add(Dense(200, activation="leaky_relu"))
model3.add(Dense(1, activation="sigmoid"))
```

[36]:
```python
model3.compile(optimizer="adam", loss="binary_crossentropy",␣
↪metrics=['accuracy'])
```

[37]:
```python
history3 = model3.fit(train_images, train_labels, validation_data=(test_images,␣
↪test_labels), epochs=30)
```

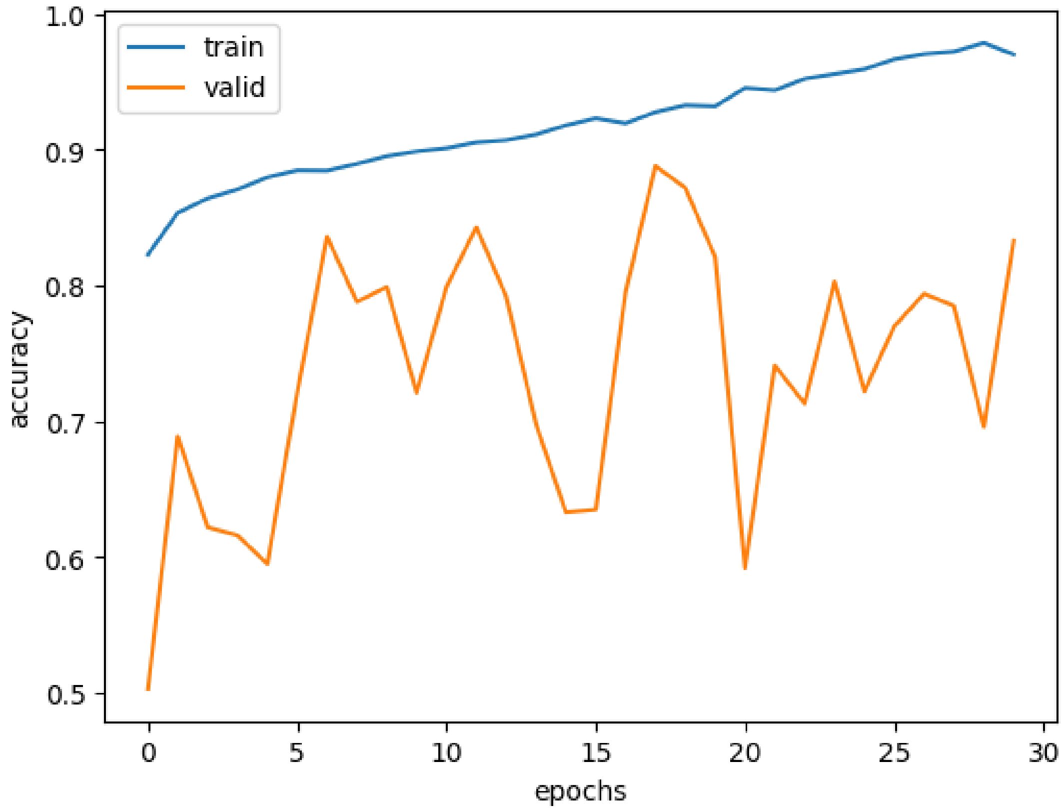
```
Epoch 1/30
301/301 [==============================] - 11s 25ms/step - loss: 0.3797 -
accuracy: 0.8228 - val_loss: 0.7430 - val_accuracy: 0.5030
Epoch 2/30
301/301 [==============================] - 7s 23ms/step - loss: 0.3304 -
accuracy: 0.8536 - val_loss: 0.5919 - val_accuracy: 0.6890
Epoch 3/30
301/301 [==============================] - 7s 24ms/step - loss: 0.3108 -
accuracy: 0.8642 - val_loss: 1.0364 - val_accuracy: 0.6220
Epoch 4/30
301/301 [==============================] - 7s 24ms/step - loss: 0.2991 -
accuracy: 0.8708 - val_loss: 0.8754 - val_accuracy: 0.6160
Epoch 5/30
301/301 [==============================] - 7s 23ms/step - loss: 0.2824 -
accuracy: 0.8798 - val_loss: 1.4004 - val_accuracy: 0.5950
Epoch 6/30
301/301 [==============================] - 7s 24ms/step - loss: 0.2716 -
accuracy: 0.8849 - val_loss: 0.8805 - val_accuracy: 0.7210
Epoch 7/30
301/301 [==============================] - 7s 23ms/step - loss: 0.2683 -
accuracy: 0.8846 - val_loss: 0.3770 - val_accuracy: 0.8360
Epoch 8/30
301/301 [==============================] - 7s 23ms/step - loss: 0.2609 -
```

```
accuracy: 0.8896 - val_loss: 0.4588 - val_accuracy: 0.7880
Epoch 9/30
301/301 [==============================] - 7s 23ms/step - loss: 0.2546 -
accuracy: 0.8953 - val_loss: 0.4617 - val_accuracy: 0.7990
Epoch 10/30
301/301 [==============================] - 7s 23ms/step - loss: 0.2410 -
accuracy: 0.8988 - val_loss: 0.4976 - val_accuracy: 0.7210
Epoch 11/30
301/301 [==============================] - 7s 23ms/step - loss: 0.2398 -
accuracy: 0.9012 - val_loss: 0.3772 - val_accuracy: 0.7990
Epoch 12/30
301/301 [==============================] - 7s 23ms/step - loss: 0.2305 -
accuracy: 0.9055 - val_loss: 0.4201 - val_accuracy: 0.8430
Epoch 13/30
301/301 [==============================] - 7s 23ms/step - loss: 0.2216 -
accuracy: 0.9071 - val_loss: 0.4559 - val_accuracy: 0.7920
Epoch 14/30
301/301 [==============================] - 7s 23ms/step - loss: 0.2162 -
accuracy: 0.9113 - val_loss: 1.5631 - val_accuracy: 0.6980
Epoch 15/30
301/301 [==============================] - 7s 24ms/step - loss: 0.2030 -
accuracy: 0.9180 - val_loss: 0.9772 - val_accuracy: 0.6330
Epoch 16/30
301/301 [==============================] - 7s 23ms/step - loss: 0.1952 -
accuracy: 0.9232 - val_loss: 1.7122 - val_accuracy: 0.6350
Epoch 17/30
301/301 [==============================] - 7s 24ms/step - loss: 0.1938 -
accuracy: 0.9195 - val_loss: 0.4995 - val_accuracy: 0.7950
Epoch 18/30
301/301 [==============================] - 7s 24ms/step - loss: 0.1821 -
accuracy: 0.9277 - val_loss: 0.3221 - val_accuracy: 0.8880
Epoch 19/30
301/301 [==============================] - 7s 24ms/step - loss: 0.1660 -
accuracy: 0.9327 - val_loss: 0.3350 - val_accuracy: 0.8720
Epoch 20/30
301/301 [==============================] - 7s 24ms/step - loss: 0.1687 -
accuracy: 0.9320 - val_loss: 0.4435 - val_accuracy: 0.8210
Epoch 21/30
301/301 [==============================] - 7s 23ms/step - loss: 0.1455 -
accuracy: 0.9455 - val_loss: 1.6938 - val_accuracy: 0.5920
Epoch 22/30
301/301 [==============================] - 7s 23ms/step - loss: 0.1383 -
accuracy: 0.9439 - val_loss: 0.7024 - val_accuracy: 0.7410
Epoch 23/30
301/301 [==============================] - 7s 23ms/step - loss: 0.1224 -
accuracy: 0.9523 - val_loss: 0.6249 - val_accuracy: 0.7130
Epoch 24/30
301/301 [==============================] - 7s 24ms/step - loss: 0.1100 -
```

```
accuracy: 0.9559 - val_loss: 0.4766 - val_accuracy: 0.8030
Epoch 25/30
301/301 [==============================] - 7s 23ms/step - loss: 0.1040 -
accuracy: 0.9594 - val_loss: 1.2222 - val_accuracy: 0.7220
Epoch 26/30
301/301 [==============================] - 7s 23ms/step - loss: 0.0892 -
accuracy: 0.9667 - val_loss: 1.1108 - val_accuracy: 0.7700
Epoch 27/30
301/301 [==============================] - 7s 23ms/step - loss: 0.0766 -
accuracy: 0.9705 - val_loss: 0.5368 - val_accuracy: 0.7940
Epoch 28/30
301/301 [==============================] - 7s 23ms/step - loss: 0.0719 -
accuracy: 0.9723 - val_loss: 1.0422 - val_accuracy: 0.7850
Epoch 29/30
301/301 [==============================] - 7s 23ms/step - loss: 0.0586 -
accuracy: 0.9787 - val_loss: 1.2243 - val_accuracy: 0.6960
Epoch 30/30
301/301 [==============================] - 7s 23ms/step - loss: 0.0766 -
accuracy: 0.9702 - val_loss: 0.5319 - val_accuracy: 0.8330
```

[38]:

```
plt.plot(history3.history["accuracy"])
plt.plot(history3.history["val_accuracy"])
plt.xlabel("epochs")
plt.ylabel("accuracy")
plt.legend(["train","valid"])
plt.show()
```



[39]:
```
y_pred3 = model3.predict(test_images)
```

```
32/32 [==============================] - 0s 7ms/step
```

[40]:
```
y_pred3 = np.where(y_pred3>0.6, 1, 0)
```

[41]:
```
y_pred3 = y_pred3.reshape(1,-1)[0]
```

[42]:
```
print(classification_report(y_pred3, test_labels))
```

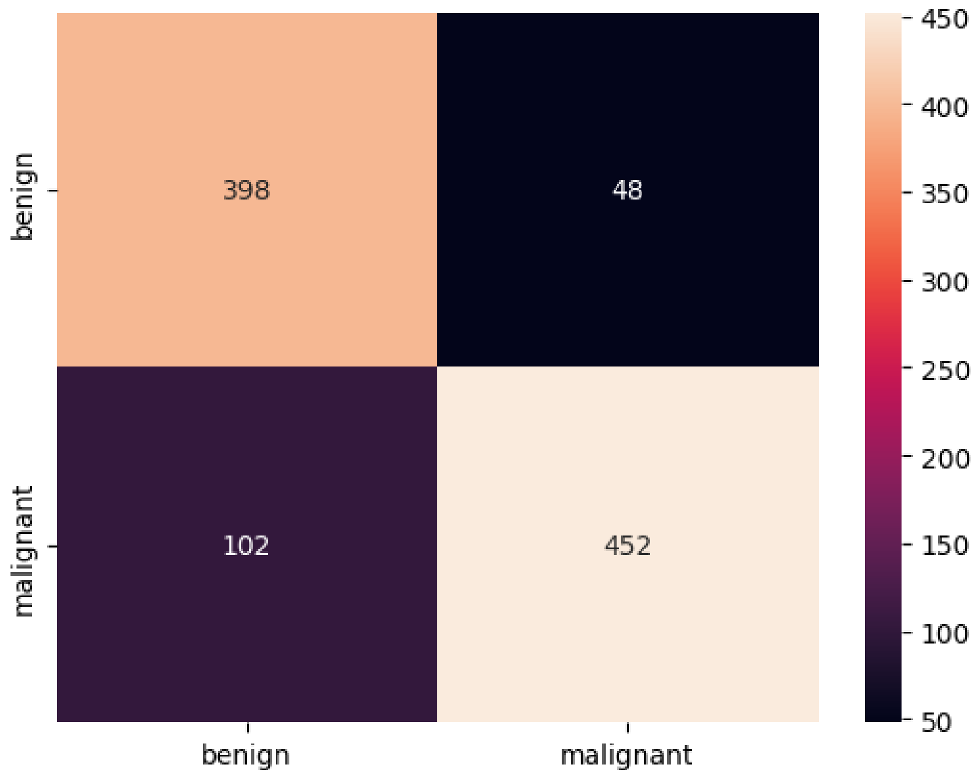
```
              precision    recall  f1-score   support

           0       0.80      0.89      0.84       446
           1       0.90      0.82      0.86       554

    accuracy                           0.85      1000
   macro avg       0.85      0.85      0.85      1000
weighted avg       0.86      0.85      0.85      1000
```

[43]:
```
sns.heatmap(confusion_matrix(y_pred3, test_labels), fmt='g', annot=True ,␣
↪xticklabels=["benign", "malignant"], yticklabels=["benign", "malignant"])
```

[43]:
```
<Axes: >
```



XGBoost Classifier

[44]:
```
xgb_clf = xgb.XGBClassifier()
```

[45]:
```
train_images_xgb = train_images.reshape(train_images.shape[0],-1)
#converting the data into 2D format as ML algorithms cannot work directly on␣
↪the images so reshaping te data
```

[46]:
```
test_images_xgb = test_images.reshape(test_images.shape[0],-1)
```

[47]:
```
print(f"shape of train images xgb {train_images_xgb.shape}")
print(f"shape of test images xgb {test_images_xgb.shape}")
```

```
shape of train images xgb (9605, 16384)
shape of test images xgb (1000, 16384)
```

[48]:
```
xgb_clf.fit(train_images_xgb, train_labels)
```

[48]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, …)
```

[50]:
```
y_pred4 = xgb_clf.predict(test_images_xgb)
```

[51]:
```
print(f"accuracy of xgboost {accuracy_score(y_pred4, test_labels)}")
```

```
accuracy of xgboost 0.905
```

[52]:
```
print(classification_report(y_pred4, test_labels))
```

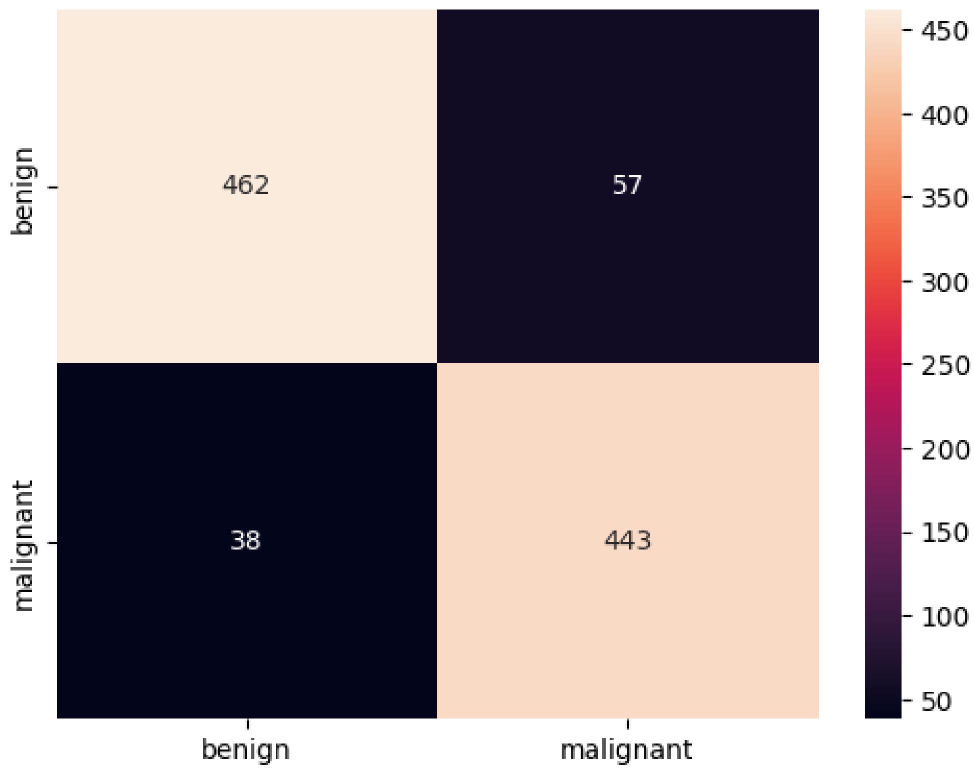
```
              precision    recall  f1-score   support

           0       0.92      0.89      0.91       519
           1       0.89      0.92      0.90       481

    accuracy                           0.91      1000
   macro avg       0.91      0.91      0.90      1000
weighted avg       0.91      0.91      0.91      1000
```

[53]:
```
sns.heatmap(confusion_matrix(y_pred4, test_labels), fmt='g', annot=True ,␣
 ↪xticklabels=["benign", "malignant"], yticklabels=["benign", "malignant"])
```

[53]:
```
<Axes: >
```



Random Forest Classifier

[54]:
```
rf_clf = RandomForestClassifier()
```

[55]:
```
rf_clf.fit(train_images_xgb, train_labels)
```

[55]:
```
RandomForestClassifier()
```

[56]:
```
y_pred5 = rf_clf.predict(test_images_xgb)
```

[57]:
```
print(f"accuracy of random forest is {accuracy_score(y_pred5, test_labels)}")
```

```
accuracy of random forest is 0.903
```

[58]:
```
print(classification_report(y_pred5, test_labels))
```

```
              precision    recall  f1-score   support

           0       0.92      0.89      0.90       521
           1       0.88      0.92      0.90       479

    accuracy                           0.90      1000
   macro avg       0.90      0.90      0.90      1000
```

```
weighted avg       0.90      0.90      0.90      1000
```

[59]:
```
sns.heatmap(confusion_matrix(y_pred5, test_labels), fmt='g', annot=True ,␣
↪xticklabels=["benign", "malignant"], yticklabels=["benign", "malignant"])
```

[59]: <Axes: >