Skin Cancer Detection - Using Transfer Learning (MobileNet)

In [1]:

```
import numpy as np
import cv2

import PIL.Image as Image
import os

import matplotlib.pylab as plt

import tensorflow as tf
import tensorflow_hub as hub

from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential

import time
```

In [2]:

```
IMAGE_SHAPE = (224, 224)
EPOCHS = 50


classifier = tf.keras.Sequential([
    hub.KerasLayer("https://tfhub.dev/google/tf2-preview/mobilenet_v2/classification/4",
])
```

In [3]:

```
random_image = Image.open("../dataset/CancerDetection/benign/3.jpg").resize(IMAGE_SHAPE)
random_image
```

Out[3]:

In [4]:

```
data_dir = '..\\dataset\\CancerDetection'
```

In [5]:

```
import pathlib
data_dir = pathlib.Path(data_dir)
data_dir
```

Out[5]:

```
WindowsPath('../dataset/CancerDetection')
```

In [6]:

```
list(data_dir.glob('*/*.jpg'))[:5]
```

Out[6]:

```
[WindowsPath('../dataset/CancerDetection/benign/1.jpg'),
 WindowsPath('../dataset/CancerDetection/benign/10.jpg'),
 WindowsPath('../dataset/CancerDetection/benign/100.jpg'),
 WindowsPath('../dataset/CancerDetection/benign/1000.jpg'),
 WindowsPath('../dataset/CancerDetection/benign/1001.jpg')]
```

In [7]:

```
image_count = len(list(data_dir.glob('*/*.jpg')))
print(image_count)
```

```
3297
```

In [8]:

```
benign_samples = list(data_dir.glob('benign/*'))
benign_samples[:5]
```

Out[8]:

```
[WindowsPath('../dataset/CancerDetection/benign/1.jpg'),
 WindowsPath('../dataset/CancerDetection/benign/10.jpg'),
 WindowsPath('../dataset/CancerDetection/benign/100.jpg'),
 WindowsPath('../dataset/CancerDetection/benign/1000.jpg'),
 WindowsPath('../dataset/CancerDetection/benign/1001.jpg')]
```

In [9]:

```
malignant_samples = list(data_dir.glob('malignant/*'))
malignant_samples[:5]
```

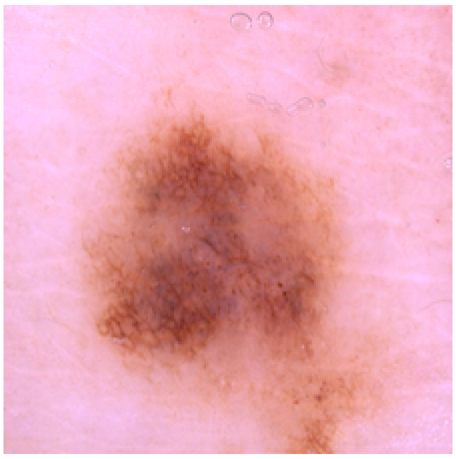
Out[9]:

```
[WindowsPath('../dataset/CancerDetection/malignant/1.jpg'),
 WindowsPath('../dataset/CancerDetection/malignant/10.jpg'),
 WindowsPath('../dataset/CancerDetection/malignant/100.jpg'),
 WindowsPath('../dataset/CancerDetection/malignant/1000.jpg'),
 WindowsPath('../dataset/CancerDetection/malignant/1001.jpg')]
```

In [10]:

```
Image.open(str(benign_samples[1]))
```

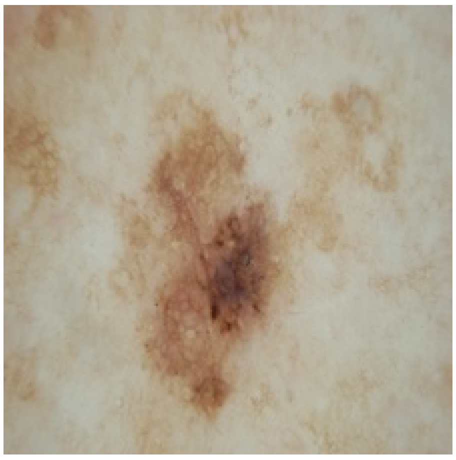
Out[10]:



In [11]:

```
Image.open(str(malignant_samples[1]))
```

Out[11]:



Reading lesion images from disk into numpy array using opencv

In [12]:

```
skin_images_dict = {
    'benign': list(data_dir.glob('benign/*')),
    'malignant': list(data_dir.glob('malignant/*')),
}
```

In [13]:

```
skin_labels_dict = {
    'benign': 0,
    'malignant': 1,
}
```

In [14]:

```
skin_images_dict['malignant'][:5]
```

Out[14]:

```
[WindowsPath('../dataset/CancerDetection/malignant/1.jpg'),
 WindowsPath('../dataset/CancerDetection/malignant/10.jpg'),
 WindowsPath('../dataset/CancerDetection/malignant/100.jpg'),
 WindowsPath('../dataset/CancerDetection/malignant/1000.jpg'),
 WindowsPath('../dataset/CancerDetection/malignant/1001.jpg')]
```

In [15]:

```
str(skin_images_dict['malignant'][0])
```

Out[15]:

```
'..\\dataset\\CancerDetection\\malignant\\1.jpg'
```

In [16]:

```
img = cv2.imread(str(skin_images_dict['malignant'][0]))
```

In [17]:

```
img.shape
```

Out[17]:

```
(224, 224, 3)
```

In [18]:

```
cv2.resize(img,(224,224)).shape
```

Out[18]:

```
(224, 224, 3)
```

In [19]:

```
X, y = [], []

for cancer_name, images in skin_images_dict.items():

    for image in images:

        img = cv2.imread(str(image))
        resized_img = cv2.resize(img,(224,224))
        X.append(resized_img)
        y.append(skin_labels_dict[cancer_name])
```

In [20]:

```
X = np.array(X)
y = np.array(y)
```

Train test split

In [21]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)
```

Preprocessing: scale images

In [22]:

```
X_train_scaled = X_train / 255
X_test_scaled = X_test / 255
```

Make prediction using pre-trained model on new dataset

In [23]:

```
X[0].shape
```

Out[23]:

```
(224, 224, 3)
```

In [24]:

```
IMAGE_SHAPE+(3,)
```

Out[24]:

```
(224, 224, 3)
```

In [25]:

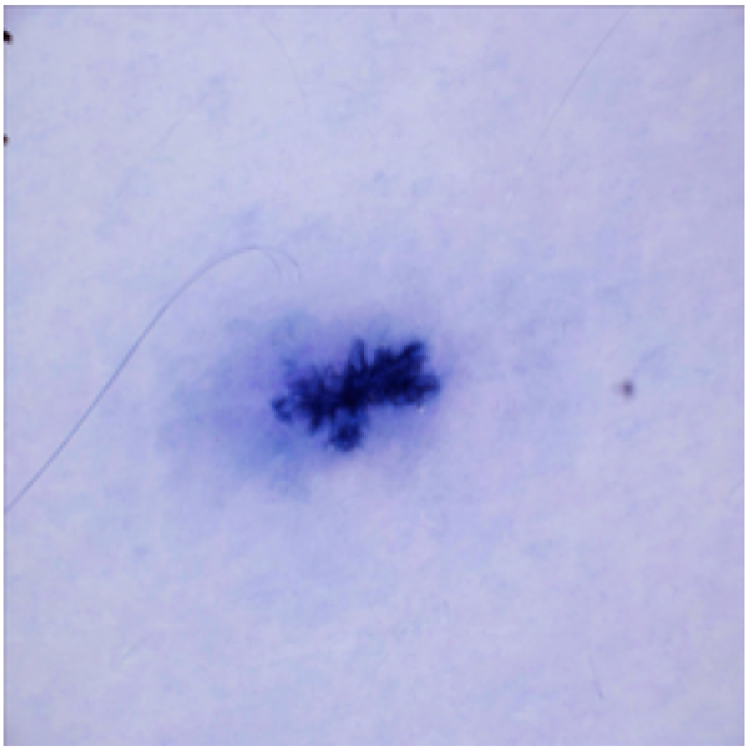
```
x0_resized = cv2.resize(X[0], IMAGE_SHAPE)
x1_resized = cv2.resize(X[1], IMAGE_SHAPE)
x2_resized = cv2.resize(X[2], IMAGE_SHAPE)
```

In [26]:

```
plt.axis('off')
plt.imshow(X[0])
```

Out[26]:

```
<matplotlib.image.AxesImage at 0x2ad026ba4a0>
```

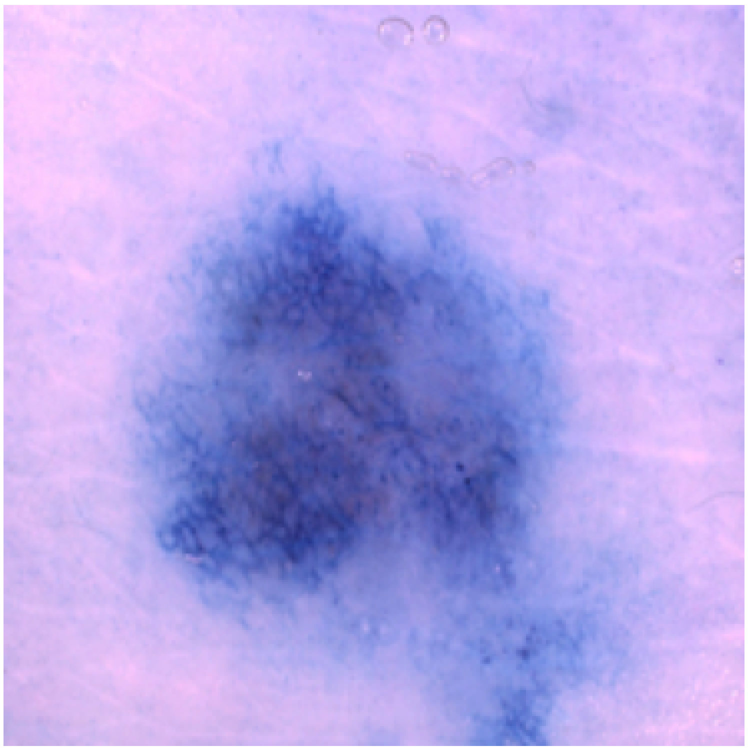


In [27]:

```
plt.axis('off')
plt.imshow(X[1])
```

Out[27]:

```
<matplotlib.image.AxesImage at 0x2ae0cc487f0>
```

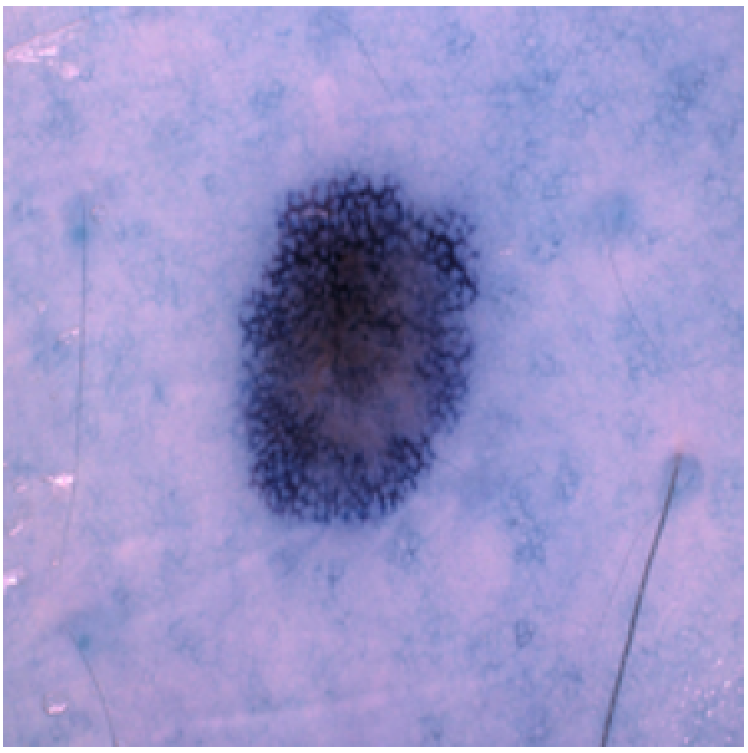


In [28]:

```
plt.axis('off')
plt.imshow(X[2])
```

Out[28]:

```
<matplotlib.image.AxesImage at 0x2acc3e72c50>
```



In [29]:

```
predicted = classifier.predict(np.array([x0_resized, x1_resized, x2_resized]))
predicted = np.argmax(predicted, axis=1)
predicted
```

```
1/1 [==============================] - 2s 2s/step
```

Out[29]:

```
array([795, 795, 795], dtype=int64)
```

In [30]:

```
# image_labels[795]
```

Now take pre-trained model and retrain it using HAM10000 images

In [31]:

```
feature_extractor_model = "https://tfhub.dev/google/tf2-preview/mobilenet_v2/feature_vec

pretrained_model_without_top_layer = hub.KerasLayer(
    feature_extractor_model, input_shape=(224, 224, 3), trainable=False)
```

In [32]:

```
cancer_classes = 2

model = tf.keras.Sequential([
  pretrained_model_without_top_layer,
  tf.keras.layers.Dense(cancer_classes)
])

model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 keras_layer_1 (KerasLayer)  (None, 1280)              2257984

 dense (Dense)               (None, 2)                 2562

=================================================================
Total params: 2,260,546
Trainable params: 2,562
Non-trainable params: 2,257,984
_________________________________________________________________
```

In [33]:

```
t0 = time.time()

model.compile(
  optimizer="adam",
  loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
  metrics=['acc']
)



history = model.fit(
    X_train_scaled,
    y_train,
    epochs=EPOCHS
)

t1 = time.time()
```

```
Epoch 1/50
78/78 [==============================] - 48s 571ms/step - loss: 0.4850 - a
cc: 0.7646
Epoch 2/50
78/78 [==============================] - 45s 575ms/step - loss: 0.3648 - a
cc: 0.8426
Epoch 3/50
78/78 [==============================] - 46s 587ms/step - loss: 0.3416 - a
cc: 0.8487
Epoch 4/50
78/78 [==============================] - 48s 614ms/step - loss: 0.3061 - a
cc: 0.8649
Epoch 5/50
78/78 [==============================] - 49s 633ms/step - loss: 0.2943 - a
cc: 0.8693
Epoch 6/50
78/78 [==============================] - 49s 633ms/step - loss: 0.2790 - a
cc: 0.8827
Epoch 7/50
78/78 [==============================] - 49s 622ms/step - loss: 0.2710 - a
cc: 0.8875
Epoch 8/50
78/78 [==============================] - 49s 626ms/step - loss: 0.2610 - a
cc: 0.8879
Epoch 9/50
78/78 [==============================] - 54s 690ms/step - loss: 0.2488 - a
cc: 0.8940
Epoch 10/50
78/78 [==============================] - 55s 699ms/step - loss: 0.2393 - a
cc: 0.8981
Epoch 11/50
78/78 [==============================] - 57s 725ms/step - loss: 0.2338 - a
cc: 0.9057
Epoch 12/50
78/78 [==============================] - 56s 724ms/step - loss: 0.2318 - a
cc: 0.9094
Epoch 13/50
78/78 [==============================] - 58s 743ms/step - loss: 0.2219 - a
cc: 0.9082
Epoch 14/50
78/78 [==============================] - 72s 927ms/step - loss: 0.2153 - a
cc: 0.9150
Epoch 15/50
78/78 [==============================] - 74s 943ms/step - loss: 0.2116 - a
cc: 0.9179
Epoch 16/50
78/78 [==============================] - 466s 6s/step - loss: 0.2074 - ac
c: 0.9142
Epoch 17/50
78/78 [==============================] - 46s 589ms/step - loss: 0.2058 - a
cc: 0.9150
Epoch 18/50
78/78 [==============================] - 42s 543ms/step - loss: 0.1996 - a
cc: 0.9235
Epoch 19/50
78/78 [==============================] - 44s 568ms/step - loss: 0.1921 - a
cc: 0.9284
Epoch 20/50
78/78 [==============================] - 47s 598ms/step - loss: 0.1928 - a
cc: 0.9288
Epoch 21/50
```

```
78/78 [==============================] - 47s 608ms/step - loss: 0.1889 - a
cc: 0.9199
Epoch 22/50
78/78 [==============================] - 48s 615ms/step - loss: 0.1875 - a
cc: 0.9252
Epoch 23/50
78/78 [==============================] - 50s 639ms/step - loss: 0.1781 - a
cc: 0.9292
Epoch 24/50
78/78 [==============================] - 54s 692ms/step - loss: 0.1765 - a
cc: 0.9316
Epoch 25/50
78/78 [==============================] - 46s 595ms/step - loss: 0.1740 - a
cc: 0.9357
Epoch 26/50
78/78 [==============================] - 47s 602ms/step - loss: 0.1723 - a
cc: 0.9328
Epoch 27/50
78/78 [==============================] - 47s 601ms/step - loss: 0.1777 - a
cc: 0.9244
Epoch 28/50
78/78 [==============================] - 49s 629ms/step - loss: 0.1634 - a
cc: 0.9373
Epoch 29/50
78/78 [==============================] - 48s 614ms/step - loss: 0.1674 - a
cc: 0.9349
Epoch 30/50
78/78 [==============================] - 50s 641ms/step - loss: 0.1579 - a
cc: 0.9417
Epoch 31/50
78/78 [==============================] - 48s 621ms/step - loss: 0.1583 - a
cc: 0.9389
Epoch 32/50
78/78 [==============================] - 50s 646ms/step - loss: 0.1537 - a
cc: 0.9434
Epoch 33/50
78/78 [==============================] - 50s 643ms/step - loss: 0.1523 - a
cc: 0.9466
Epoch 34/50
78/78 [==============================] - 50s 647ms/step - loss: 0.1587 - a
cc: 0.9405
Epoch 35/50
78/78 [==============================] - 52s 665ms/step - loss: 0.1481 - a
cc: 0.9474
Epoch 36/50
78/78 [==============================] - 53s 677ms/step - loss: 0.1507 - a
cc: 0.9466
Epoch 37/50
78/78 [==============================] - 53s 680ms/step - loss: 0.1456 - a
cc: 0.9474
Epoch 38/50
78/78 [==============================] - 56s 716ms/step - loss: 0.1627 - a
cc: 0.9316
Epoch 39/50
78/78 [==============================] - 55s 706ms/step - loss: 0.1505 - a
cc: 0.9474
Epoch 40/50
78/78 [==============================] - 58s 744ms/step - loss: 0.1417 - a
cc: 0.9462
Epoch 41/50
78/78 [==============================] - 60s 774ms/step - loss: 0.1435 - a
```

```
cc: 0.9486
Epoch 42/50
78/78 [==============================] - 72s 922ms/step - loss: 0.1368 - a
cc: 0.9494
Epoch 43/50
78/78 [==============================] - 76s 974ms/step - loss: 0.1370 - a
cc: 0.9502
Epoch 44/50
78/78 [==============================] - 53s 677ms/step - loss: 0.1326 - a
cc: 0.9555
Epoch 45/50
78/78 [==============================] - 46s 588ms/step - loss: 0.1333 - a
cc: 0.9523
Epoch 46/50
78/78 [==============================] - 47s 605ms/step - loss: 0.1271 - a
cc: 0.9587
Epoch 47/50
78/78 [==============================] - 47s 606ms/step - loss: 0.1242 - a
cc: 0.9620
Epoch 48/50
78/78 [==============================] - 48s 611ms/step - loss: 0.1253 - a
cc: 0.9571
Epoch 49/50
78/78 [==============================] - 49s 629ms/step - loss: 0.1214 - a
cc: 0.9616
Epoch 50/50
78/78 [==============================] - 50s 643ms/step - loss: 0.1282 - a
cc: 0.9567
```

Training Time

In [34]:

```
print("Transfer Learning Model Training time:  ", (t1-t0)/60 , "minutes")
```

```
Transfer Learning Model Training time:   50.502716644605 minutes
```

Evaluation

In [35]:

```
model.evaluate(X_test_scaled,y_test)
```

```
26/26 [==============================] - 21s 724ms/step - loss: 0.3799 - a
cc: 0.8582
```

Out[35]:

```
[0.37987974286079407, 0.8581818342208862]
```

Prediction

In [36]:

```
predicted = model.predict(X_test_scaled)
```

```
26/26 [==============================] - 18s 650ms/step
```

In [37]:

```
# print(predicted)
print(len(predicted))
print(len(y_test))
```

```
825
825
```

In [38]:

```
confidence = np.max(predicted, axis=1)
predictions = np.argmax(predicted, axis=1)
```

In [39]:

```
# print(predictions)
# print(y_test)
```

Plotting History

In [40]:

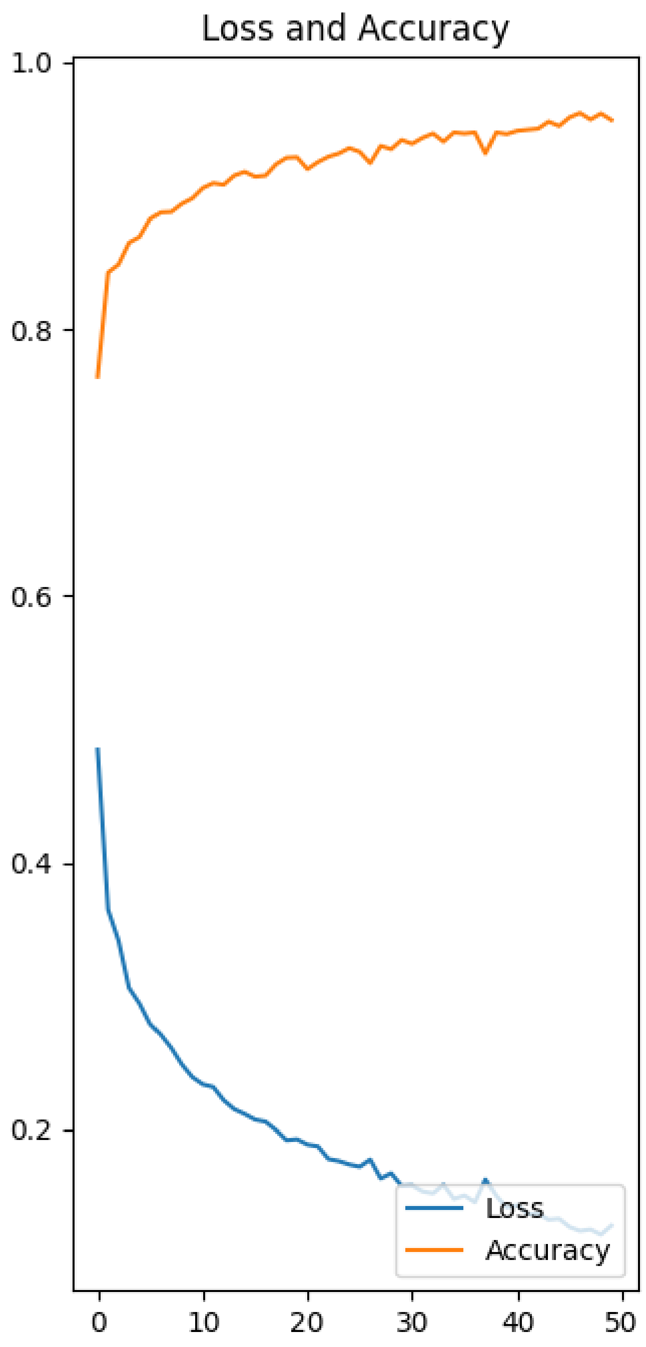
```
acc = history.history['loss']
val_acc = history.history['acc']
```

In [46]:

```
plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(range(EPOCHS), acc, label='Loss')
plt.plot(range(EPOCHS), val_acc, label='Accuracy')
plt.legend(loc='lower right')
plt.title('Loss and Accuracy')
```

Out[46]:

```
Text(0.5, 1.0, 'Loss and Accuracy')
```



CONFUSION MATRIX

In [42]:

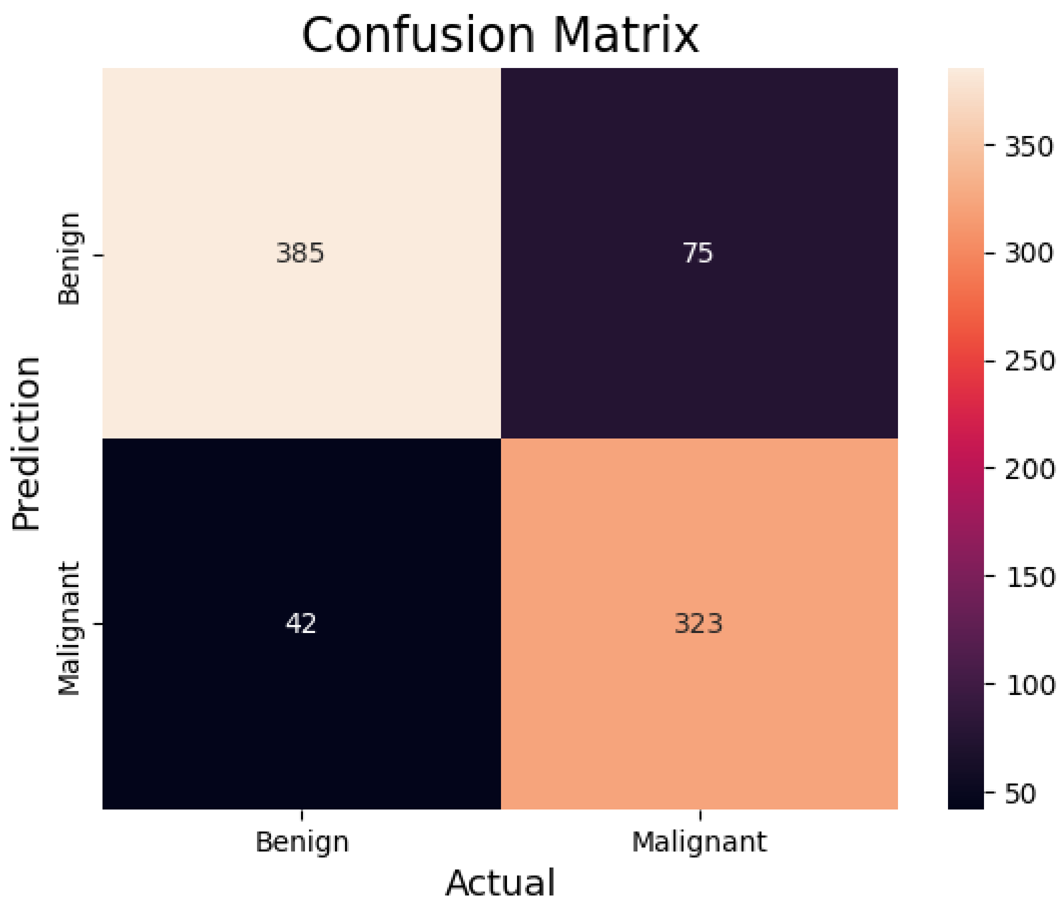
```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
```

In [43]:

```
cm = confusion_matrix(y_test, predictions)


sns.heatmap(
    cm,
    annot=True,
    fmt='g',
    xticklabels=['Benign','Malignant'],
    yticklabels=['Benign','Malignant']
)

plt.ylabel('Prediction',fontsize=13)
plt.xlabel('Actual',fontsize=13)
plt.title('Confusion Matrix',fontsize=17)
plt.show()
```



In [44]:

```
from sklearn.metrics import classification_report
print(classification_report(y_test, predictions))
```

```
              precision    recall  f1-score   support

           0       0.90      0.84      0.87       460
           1       0.81      0.88      0.85       365

    accuracy                           0.86       825
   macro avg       0.86      0.86      0.86       825
weighted avg       0.86      0.86      0.86       825
```

Saving the Model

In [45]:

```
import os
# model_version=max([int(i) for i in os.listdir("../transfer_savedmodels") + [0]])+1
model.save(f"../transfer_savedmodels/final.h5")
```

In [ ]:

```
```