Project 5 - Deep Learning and Reinforcement Learning

Objective

The main objective of my project is to focus on Deep Learning using CNN ARchitecture. The analysis and classification will help detect lung cancer based on the CT scan images.

About Dataset

The Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD) lung cancer dataset was collected in the above-mentioned specialist hospitals over a period of three months in fall 2019. It includes CT scans of patients diagnosed with lung cancer in different stages, as well as healthy subjects. IQ-OTH/NCCD slides were marked by oncologists and radiologists in these two centers. The dataset contains a total of 1190 images representing CT scan slices of 110 cases. These cases are grouped into three classes: normal, benign, and malignant. of these, 40 cases are diagnosed as malignant; 15 cases diagnosed with benign, and 55 cases classified as normal cases. The CT scans were originally collected in DICOM format. The scanner used is SOMATOM from Siemens. CT protocol includes: 120 kV, slice thickness of 1 mm, with window width ranging from 350 to 1200 HU a and window center from 50 to 600 were used for reading. with breath-hold at full inspiration. All images were de-identified before performing analysis. Written consent was waived by the oversight review board. The study was approved by the institutional review board of participating medical centers. Each scan contains several slices. The number of these slices range from 80 to 200 slices, each of them represents an image of the human chest with different sides and angles. The 110 cases vary in gender, age, educational attainment, area of residence, and living status. Some of them are employees of the Iraqi ministries of Transport and Oil, others are farmers and gainers. Most of them come from places in the middle region of Iraq, particularly, the provinces of Baghdad, Wasit, Diyala, Salahuddin, and Babylon.

Import Packages

In [1]:
```
%config Completer.use_jedi = False
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
from PIL import Image
import seaborn as sns
import cv2
import random
import os
import imageio
import plotly.graph_objects as go
import plotly.express as px
import plotly.figure_factory as ff
from plotly.subplots import make_subplots
from collections import Counter

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.neighbors import LocalOutlierFactor
from sklearn.metrics import accuracy_score, recall_score, precision_score, classification_report, confusion_matrix, plot_confusic
from sklearn.model_selection import RandomizedSearchCV, cross_val_score, RepeatedStratifiedKFold
from imblearn.over_sampling import SMOTE

import tensorflow as tf
import tensorflow_addons as tfa
import keras
from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation, Flatten
from keras.layers import Conv2D, MaxPooling2D, GlobalAveragePooling2D, BatchNormalization
from keras.applications.resnet import ResNet50
from keras.preprocessing.image import ImageDataGenerator, load_img, img_to_array, array_to_img
```

Image Size Variations

In [3]:
```python
size_data = {}
for i in categories:
    path = os.path.join(directory, i)
    class_num = categories.index(i)
    temp_dict = {}
    for file in os.listdir(path):
        filepath = os.path.join(path, file)
        height, width, channels = imageio.imread(filepath).shape
        if str(height) + ' x ' + str(width) in temp_dict:
            temp_dict[str(height) + ' x ' + str(width)] += 1
        else:
            temp_dict[str(height) + ' x ' + str(width)] = 1

    size_data[i] = temp_dict

size_data
```

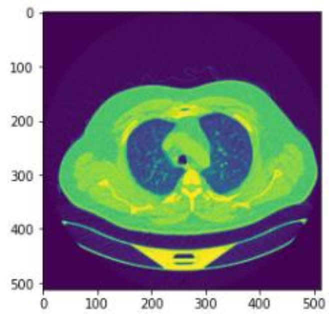
Out[3]:
```
{'Bengin cases': {'512 x 512': 120},
 'Malignant cases': {'512 x 512': 501,
  '512 x 623': 31,
  '512 x 801': 28,
  '404 x 511': 1},
 'Normal cases': {'512 x 512': 415, '331 x 506': 1}}
```

Observations

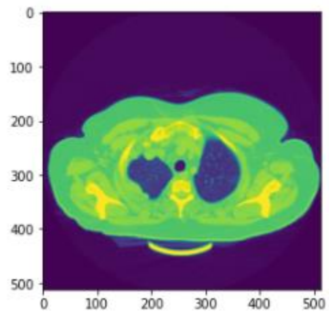
As the image data varies in shape, we have to normalize all to same value for training. Best size of image can be 256x256.

In [4]:
```python
for i in categories:
    path = os.path.join(directory, i)
    class_num = categories.index(i)
    for file in os.listdir(path):
        filepath = os.path.join(path, file)
        print(i)
        img = cv2.imread(filepath, 0)
        plt.imshow(img)
        plt.show()
        break
```

```
Bengin cases
```




```
Malignant cases
```



Normal cases

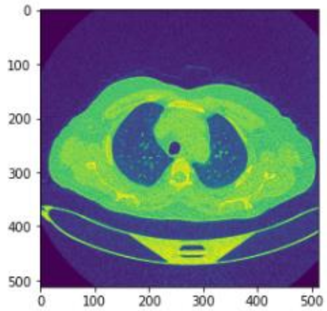
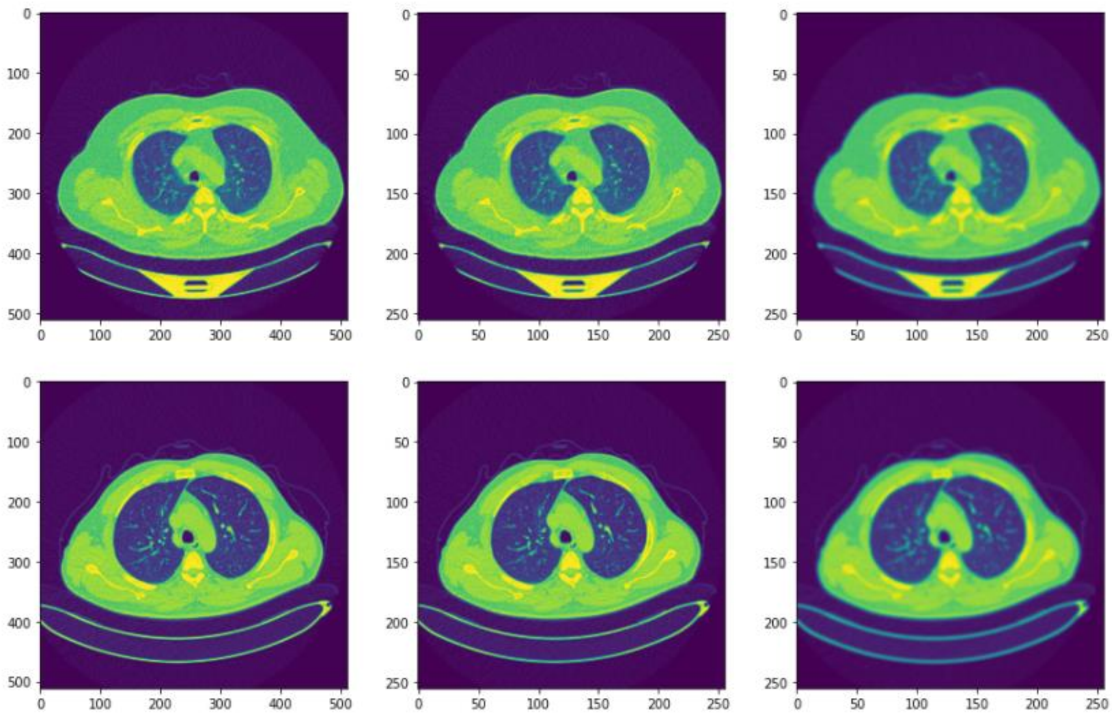


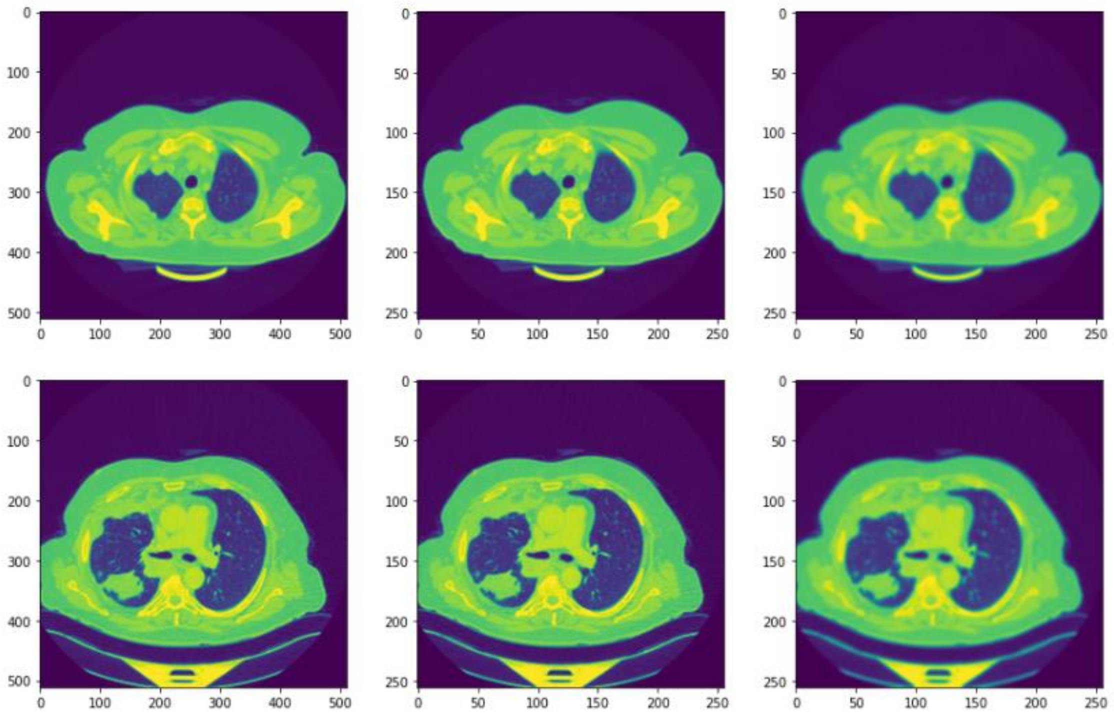
Image Preprocessing and Testing

In [5]:
```
img_size = 256
for i in categories:
    cnt, samples = 0, 3
    fig, ax = plt.subplots(samples, 3, figsize=(15, 15))
    fig.suptitle(i)

    path = os.path.join(directory, i)
    class_num = categories.index(i)
    for curr_cnt, file in enumerate(os.listdir(path)):
        filepath = os.path.join(path, file)
        img = cv2.imread(filepath, 0)

        img0 = cv2.resize(img, (img_size, img_size))

        img1 = cv2.GaussianBlur(img0, (5, 5), 0)

        ax[cnt, 0].imshow(img)
        ax[cnt, 1].imshow(img0)
        ax[cnt, 2].imshow(img1)
        cnt += 1
        if cnt == samples:
            break

plt.show()
```

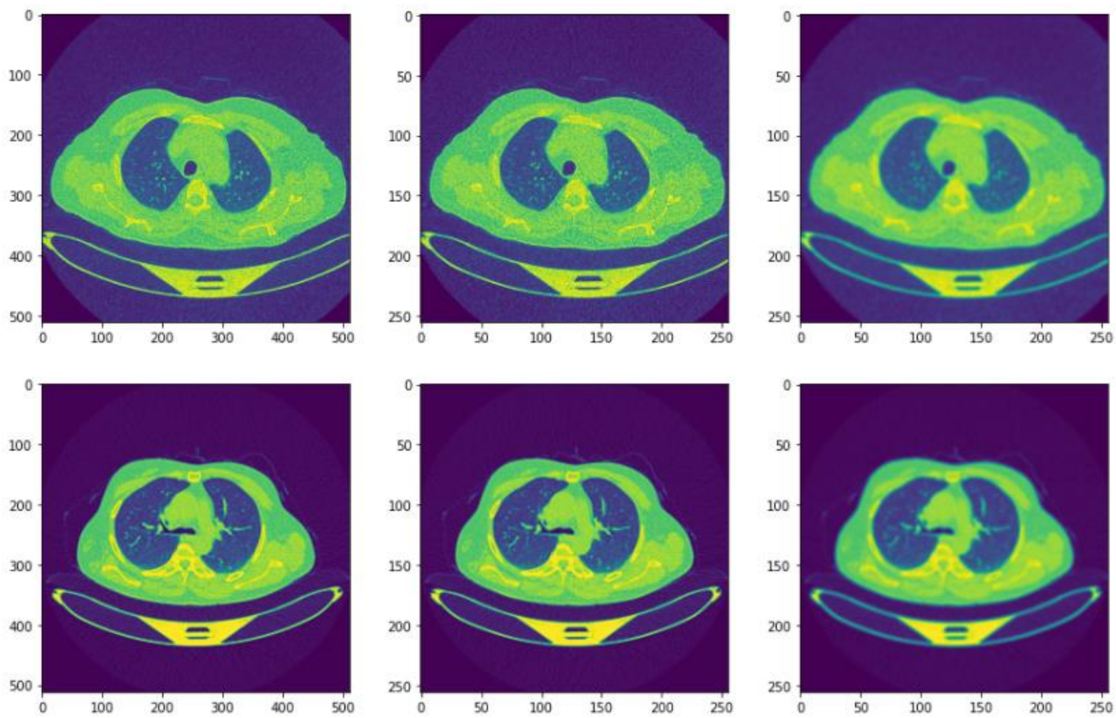
Bengin cases



Malignant cases



Normal cases



Model Building Strategy

I have designed 3 ways of architecture along with differentiable training data as the data I'm using is imbalanced among classes.

1. As the data is imbalanced, the first approach is using **SMOTE** to oversampling the minority classes.
2. Second approach is to use **Class Weights** making the model to differentiate and bias towards minority class.
3. To add data, third approach uses **Data Augmentation.** As I'm using medical reports, the augmentation options are limited to dual axes flips only.

Preparing Data

In [6]:
```
data = []
img_size = 256

for i in categories:
    path = os.path.join(directory, i)
    class_num = categories.index(i)
    for file in os.listdir(path):
        filepath = os.path.join(path, file)
        img = cv2.imread(filepath, 0)
        # preprocess here
        img = cv2.resize(img, (img_size, img_size))
        data.append([img, class_num])

random.shuffle(data)

X, y = [], []
for feature, label in data:
    X.append(feature)
    y.append(label)

print('X length:', len(X))
print('y counts:', Counter(y))

# normalize
X = np.array(X).reshape(-1, img_size, img_size, 1)
X = X / 255.0
y = np.array(y)
```

```
X length: 1097
y counts: Counter({1: 561, 2: 416, 0: 120})
```

In [7]:
```
X_train, X_valid, y_train, y_valid = train_test_split(X, y, random_state=10, stratify=y)

print(len(X_train), X_train.shape)
print(len(X_valid), X_valid.shape)
```

```
822 (822, 256, 256, 1)
275 (275, 256, 256, 1)
```

Applying SMOTE to oversample the data

In [8]:
```
print(Counter(y_train), Counter(y_valid))
```

```
Counter({1: 420, 2: 312, 0: 90}) Counter({1: 141, 2: 104, 0: 30})
```

In [9]:
```
print(len(X_train), X_train.shape)

X_train = X_train.reshape(X_train.shape[0], img_size*img_size*1)

print(len(X_train), X_train.shape)
```

```
822 (822, 256, 256, 1)
822 (822, 65536)
```

In [10]:
```
print('Before SMOTE:', Counter(y_train))
smote = SMOTE()
X_train_sampled, y_train_sampled = smote.fit_resample(X_train, y_train)
print('After SMOTE:', Counter(y_train_sampled))
```

```
Before SMOTE: Counter({1: 420, 2: 312, 0: 90})
After SMOTE: Counter({2: 420, 1: 420, 0: 420})
```

In [11]:
```
X_train = X_train.reshape(X_train.shape[0], img_size, img_size, 1)
X_train_sampled = X_train_sampled.reshape(X_train_sampled.shape[0], img_size, img_size, 1)

print(len(X_train), X_train.shape)
print(len(X_train_sampled), X_train_sampled.shape)
```

```
822 (822, 256, 256, 1)
1260 (1260, 256, 256, 1)
```

Model Building with SMOTE data

In [12]:
```
model1 = Sequential()

model1.add(Conv2D(64, (3, 3), input_shape=X_train.shape[1:]))
model1.add(Activation('relu'))
model1.add(MaxPooling2D(pool_size=(2, 2)))

model1.add(Conv2D(64, (3, 3), activation='relu'))
model1.add(MaxPooling2D(pool_size=(2, 2)))

model1.add(Flatten())
model1.add(Dense(16))
model1.add(Dense(3, activation='softmax'))

model1.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 254, 254, 64)      640
_________________________________________________________________
activation (Activation)      (None, 254, 254, 64)      0
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 127, 127, 64)      0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 125, 125, 64)      36928
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 62, 62, 64)        0
_________________________________________________________________
flatten (Flatten)            (None, 246016)            0
_________________________________________________________________
dense (Dense)                (None, 16)                3936272
_________________________________________________________________
dense_1 (Dense)              (None, 3)                 51
=================================================================
Total params: 3,973,891
Trainable params: 3,973,891
Non-trainable params: 0
_________________________________________________________________
```

In [13]:
```
model1.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

In [14]:
```
history = model1.fit(X_train_sampled, y_train_sampled, batch_size=8, epochs=10, validation_data=(X_valid, y_valid))
```

```
2021-11-30 18:01:40.004451: I tensorflow/compiler/mlir/mlir_graph_optimization_pass.cc:185] None of the MLIR Optimization Passe
s are enabled (registered 2)
```

```
Epoch 1/10
```

```
2021-11-30 18:01:41.415383: I tensorflow/stream_executor/cuda/cuda_dnn.cc:369] Loaded cuDNN version 8005
```

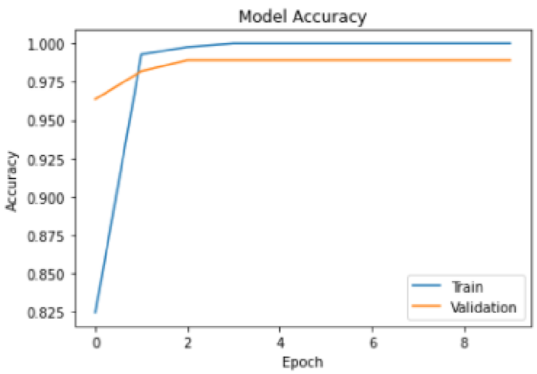
```
158/158 [==============================] - 10s 19ms/step - loss: 0.6241 - accuracy: 0.8246 - val_loss: 0.1110 - val_accuracy:
0.9636
Epoch 2/10
158/158 [==============================] - 2s 16ms/step - loss: 0.0341 - accuracy: 0.9929 - val_loss: 0.0734 - val_accuracy: 0.
9818
Epoch 3/10
158/158 [==============================] - 3s 16ms/step - loss: 0.0194 - accuracy: 0.9976 - val_loss: 0.0612 - val_accuracy: 0.
9891
Epoch 4/10
158/158 [==============================] - 2s 16ms/step - loss: 7.9046e-04 - accuracy: 1.0000 - val_loss: 0.0664 - val_accurac
y: 0.9891
Epoch 5/10
158/158 [==============================] - 3s 16ms/step - loss: 9.1531e-04 - accuracy: 1.0000 - val_loss: 0.0486 - val_accurac
y: 0.9891
Epoch 6/10
158/158 [==============================] - 3s 16ms/step - loss: 1.4046e-04 - accuracy: 1.0000 - val_loss: 0.0504 - val_accurac
y: 0.9891
Epoch 7/10
158/158 [==============================] - 3s 16ms/step - loss: 1.2933e-04 - accuracy: 1.0000 - val_loss: 0.0486 - val_accurac
y: 0.9891
Epoch 8/10
158/158 [==============================] - 3s 16ms/step - loss: 1.1861e-04 - accuracy: 1.0000 - val_loss: 0.0569 - val_accurac
y: 0.9891
Epoch 9/10
158/158 [==============================] - 2s 16ms/step - loss: 8.7605e-05 - accuracy: 1.0000 - val_loss: 0.0533 - val_accurac
y: 0.9891
Epoch 10/10
158/158 [==============================] - 3s 16ms/step - loss: 5.8848e-05 - accuracy: 1.0000 - val_loss: 0.0581 - val_accurac
y: 0.9891
```

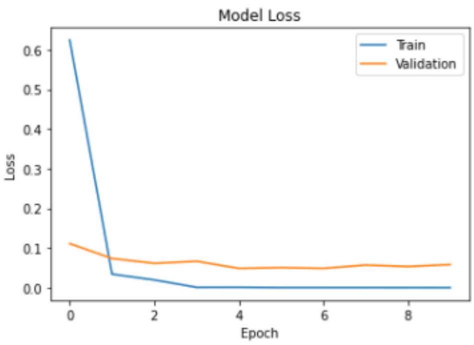
Results

In [15]:
```
y_pred = model1.predict(X_valid, verbose=1)
y_pred_bool = np.argmax(y_pred, axis=1)

print(classification_report(y_valid, y_pred_bool))

print(confusion_matrix(y_true=y_valid, y_pred=y_pred_bool))
```

```
9/9 [==============================] - 1s 30ms/step
              precision    recall  f1-score   support

           0       1.00      0.93      0.97        30
           1       0.99      1.00      1.00       141
           2       0.98      0.99      0.99       104

    accuracy                           0.99       275
   macro avg       0.99      0.97      0.98       275
weighted avg       0.99      0.99      0.99       275

[[ 28   0   2]
 [  0 141   0]
 [  0   1 103]]
```

In [16]:
```
plt.plot(history.history['accuracy'], label='Train')
plt.plot(history.history['val_accuracy'], label='Validation')
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.show()

plt.plot(history.history['loss'], label='Train')
plt.plot(history.history['val_loss'], label='Validation')
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend()
plt.show()
```





Model Building with Class Weighted Approach

In [17]:
```
model2 = Sequential()

model2.add(Conv2D(64, (3, 3), input_shape=X_train.shape[1:]))
model2.add(Activation('relu'))
model2.add(MaxPooling2D(pool_size=(2, 2)))

model2.add(Conv2D(64, (3, 3), activation='relu'))
model2.add(MaxPooling2D(pool_size=(2, 2)))

model2.add(Flatten())
model2.add(Dense(16))
model2.add(Dense(3, activation='softmax'))

model2.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_2 (Conv2D)            (None, 254, 254, 64)      640
_________________________________________________________________
activation_1 (Activation)    (None, 254, 254, 64)      0
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 127, 127, 64)      0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 125, 125, 64)      36928
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 62, 62, 64)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 246016)            0
_________________________________________________________________
dense_2 (Dense)              (None, 16)                3936272
_________________________________________________________________
dense_3 (Dense)              (None, 3)                 51
=================================================================
Total params: 3,973,891
Trainable params: 3,973,891
Non-trainable params: 0
_________________________________________________________________
```

In [18]:
```
model2.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

In [19]:
```
new_weights = {
    0: X_train.shape[0]/(3*Counter(y_train)[0]),
    1: X_train.shape[0]/(3*Counter(y_train)[1]),
    2: X_train.shape[0]/(3*Counter(y_train)[2]),
}

# new_weights[0] = 0.5
# new_weights[1] = 20

new_weights
```

Out[19]:
```
{0: 3.0444444444444443, 1: 0.6523809523809524, 2: 0.8782051282051282}
```

In [20]:
```
history = model2.fit(X_train, y_train, batch_size=8, epochs=10, validation_data=(X_valid, y_valid), class_weight=new_weights)
```

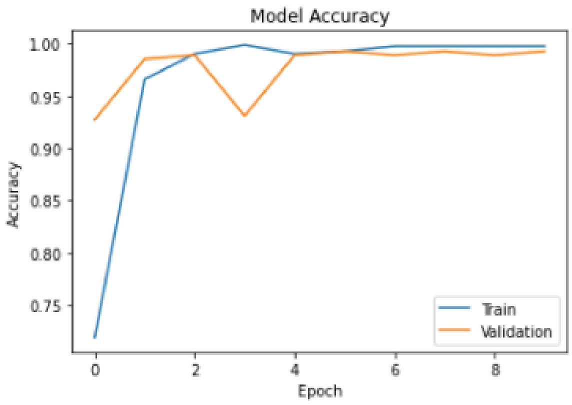
```
Epoch 1/10
103/103 [==============================] - 2s 21ms/step - loss: 1.0523 - accuracy: 0.7190 - val_loss: 0.2092 - val_accuracy: 0.
9273
Epoch 2/10
103/103 [==============================] - 2s 17ms/step - loss: 0.1291 - accuracy: 0.9659 - val_loss: 0.0582 - val_accuracy: 0.
9855
Epoch 3/10
103/103 [==============================] - 2s 17ms/step - loss: 0.0324 - accuracy: 0.9903 - val_loss: 0.0535 - val_accuracy: 0.
9891
Epoch 4/10
103/103 [==============================] - 2s 17ms/step - loss: 0.0078 - accuracy: 0.9988 - val_loss: 0.1668 - val_accuracy: 0.
9309
Epoch 5/10
103/103 [==============================] - 2s 17ms/step - loss: 0.0412 - accuracy: 0.9903 - val_loss: 0.0635 - val_accuracy: 0.
9891
Epoch 6/10
103/103 [==============================] - 2s 17ms/step - loss: 0.0337 - accuracy: 0.9927 - val_loss: 0.0938 - val_accuracy: 0.
9927
Epoch 7/10
103/103 [==============================] - 2s 17ms/step - loss: 0.0306 - accuracy: 0.9976 - val_loss: 0.0455 - val_accuracy: 0.
9891
Epoch 8/10
103/103 [==============================] - 2s 17ms/step - loss: 0.0107 - accuracy: 0.9976 - val_loss: 0.0773 - val_accuracy: 0.
9927
Epoch 9/10
103/103 [==============================] - 2s 17ms/step - loss: 0.0144 - accuracy: 0.9976 - val_loss: 0.0211 - val_accuracy: 0.
9891
Epoch 10/10
103/103 [==============================] - 2s 17ms/step - loss: 0.0189 - accuracy: 0.9976 - val_loss: 0.1001 - val_accuracy: 0.
9927
```

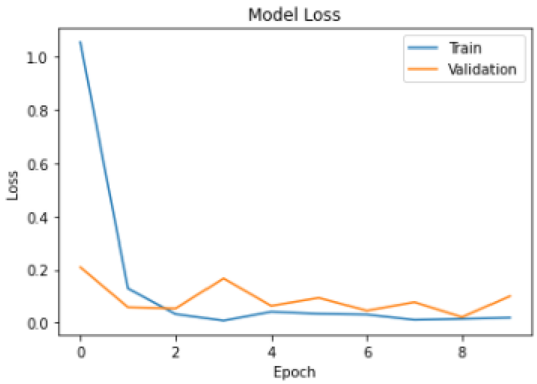
Results

In [21]:
```
y_pred = model2.predict(X_valid, verbose=1)
y_pred_bool = np.argmax(y_pred, axis=1)

print(classification_report(y_valid, y_pred_bool))

print(confusion_matrix(y_true=y_valid, y_pred=y_pred_bool))
```

```
9/9 [==============================] - 0s 14ms/step
              precision    recall  f1-score   support

           0       1.00      0.93      0.97        30
           1       1.00      1.00      1.00       141
           2       0.98      1.00      0.99       104

    accuracy                           0.99       275
   macro avg       0.99      0.98      0.99       275
weighted avg       0.99      0.99      0.99       275

[[ 28   0   2]
 [  0 141   0]
 [  0   0 104]]
```

In [22]:
```
plt.plot(history.history['accuracy'], label='Train')
plt.plot(history.history['val_accuracy'], label='Validation')
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.show()

plt.plot(history.history['loss'], label='Train')
plt.plot(history.history['val_loss'], label='Validation')
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend()
plt.show()
```





Data Augmentation

In [49]:
```
train_datagen = ImageDataGenerator(horizontal_flip=True, vertical_flip=True)
val_datagen = ImageDataGenerator()
```

In [50]:
```
train_generator = train_datagen.flow(X_train, y_train, batch_size=8)
val_generator = val_datagen.flow(X_valid, y_valid, batch_size=8)
```

In [51]:
```
model3 = Sequential()

model3.add(Conv2D(64, (3, 3), input_shape=X_train.shape[1:]))
model3.add(Activation('relu'))
model3.add(MaxPooling2D(pool_size=(2, 2)))

model3.add(Conv2D(64, (3, 3), activation='relu'))
model3.add(MaxPooling2D(pool_size=(2, 2)))

model3.add(Flatten())
model3.add(Dense(16))
model3.add(Dense(3, activation='softmax'))

model3.summary()
```

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_10 (Conv2D)           (None, 254, 254, 64)      640       
_________________________________________________________________
activation_5 (Activation)    (None, 254, 254, 64)      0         
_________________________________________________________________
max_pooling2d_10 (MaxPooling (None, 127, 127, 64)      0         
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 125, 125, 64)      36928     
_________________________________________________________________
max_pooling2d_11 (MaxPooling (None, 62, 62, 64)        0         
_________________________________________________________________
flatten_5 (Flatten)          (None, 246016)            0         
_________________________________________________________________
dense_10 (Dense)             (None, 16)                3936272   
_________________________________________________________________
dense_11 (Dense)             (None, 3)                 51        
=================================================================
Total params: 3,973,891
Trainable params: 3,973,891
Non-trainable params: 0
_________________________________________________________________
```

In [52]:
```
model3.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

In [53]:
```
history = model3.fit_generator(train_generator, epochs=5, validation_data=val_generator, class_weight=new_weights)
```

```
Epoch 1/5
103/103 [==============================] - 2s 19ms/step - loss: 1.2547 - accuracy: 0.5109 - val_loss: 0.7006 - val_accuracy: 0.
7164
Epoch 2/5
103/103 [==============================] - 2s 17ms/step - loss: 0.5844 - accuracy: 0.7676 - val_loss: 0.4634 - val_accuracy: 0.
8073
Epoch 3/5
103/103 [==============================] - 2s 17ms/step - loss: 0.3401 - accuracy: 0.8625 - val_loss: 0.3227 - val_accuracy: 0.
8655
Epoch 4/5
103/103 [==============================] - 2s 18ms/step - loss: 0.2402 - accuracy: 0.9258 - val_loss: 0.1699 - val_accuracy: 0.
9491
Epoch 5/5
103/103 [==============================] - 2s 18ms/step - loss: 0.1968 - accuracy: 0.9477 - val_loss: 0.1099 - val_accuracy: 0.
9636
```

In [54]:
```
y_pred = model3.predict(X_valid, verbose=1)
y_pred_bool = np.argmax(y_pred, axis=1)

print(classification_report(y_valid, y_pred_bool))

print(confusion_matrix(y_true=y_valid, y_pred=y_pred_bool))
```

```
9/9 [==============================] - 0s 13ms/step
              precision    recall  f1-score   support

           0       0.96      0.83      0.89        30
           1       0.97      0.99      0.98       141
           2       0.95      0.96      0.96       104

    accuracy                           0.96       275
   macro avg       0.96      0.93      0.94       275
weighted avg       0.96      0.96      0.96       275

[[ 25   0   5]
 [  1 140   0]
 [  0   4 100]]
```

Key Findings that describes the Best Model

As mentioned earlier, I have used 3 approaches to train over the dataset. All the 3 models showed significant results.

Models	Accuracy	Recall
SMOTE Model	98%	97%
Class Weights Model	99%	98%
Data Augmented Model	96%	93%

The **Class Weights Approach** works efficiently in terms of Accuracy and Recall. The accuracy is 99% and recall score 98%. Over here I have considered Recall Score because the project objective is to predict lung cancer and in a medical prediction recall score plays a vital role in describing the False Negative cases.

Future Scope

- Ahead I have plans to experiment with Transfer Learning and use ResNet or VGG16 with my model.
- Also to get more understanding on CNN parameters, I'm planning to experiment with different values for CNN parameters.