# NETAJI SUBHAS UNIVERSITY OF TECHNOLOGY, EAST CAMPUS


# Pituitary Tumour Detection in Brain using Machine Learning

## Semester 06

**ECAM 02**

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# ABSTRACT

A Brain tumour is considered as one of the aggressive diseases, among children and adults. Brain tumours account for 85 to 90 percent of all primary Central Nervous System (CNS) tumours. Every year, around 11,700 people are diagnosed with a brain tumour. The 5-year survival rate for people with a cancerous brain or CNS tumour is approximately 34 percent for men and36 percent for women. Brain Tumours are classified as: Benign Tumour, Malignant Tumour, Pituitary Tumour, etc. Proper treatment, planning, and accurate diagnostics should be implemented to improve the life expectancy of the patients.

The best technique to detect brain tumours is Magnetic Resonance Imaging (MRI). A huge amount of image data is generated through the scans. These images are examined by the radiologist. A manual examination can be error-prone due to the level of complexities involved in brain tumours and them properties.
Application of automated classification techniques using Machine Learning (ML) and Artificial Intelligence (AI)has consistently shown higher accuracy than manual classification.

Hence, proposing a system performing detection and classification by using Deep Learning Algorithms using Convolution-Neural Network (CNN), Artificial Neural Network (ANN), and Transfer Learning (TL) would be helpful to doctors all around the world.

# INTRODUCTION

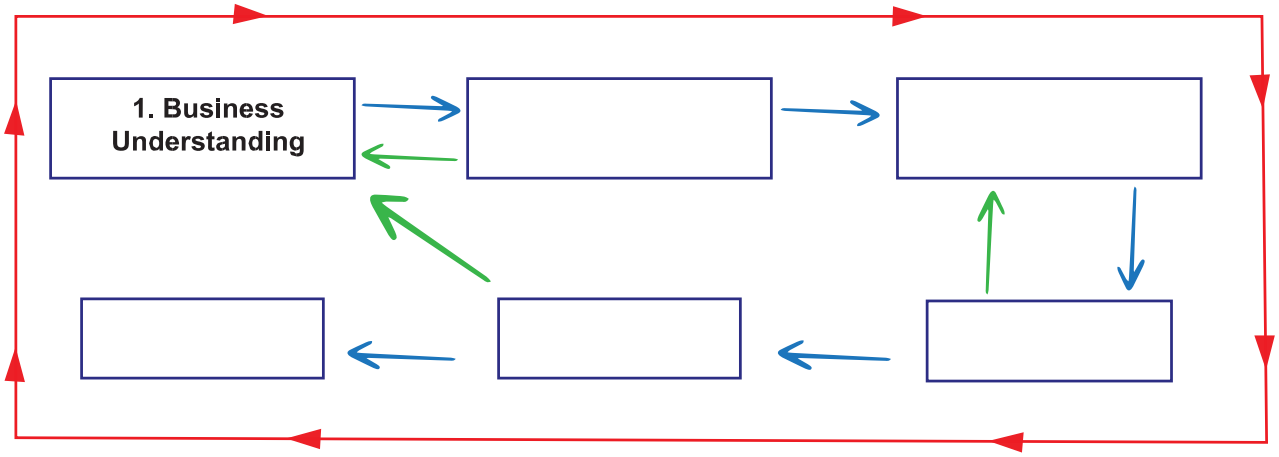
The human body is composed of numerous types of cells. Each cell has a specific function. These cells in the body grow and divide in an arranged manner and form some new cells. These new cells help to keep the human body healthy and ensures proper functioning. When some of the cells lose them ability to control their growth, they grow without any order. The extra cells formed form a mass of tissue which is called tumour. A brain tumour is a collection of abnormal cells in the brain.

Tumours can be benign or malignant. Malignant tumours lead to cancer while benign tumours are not cancerous.

The conventional method for tumour detection in magnetic resonance brain images is human inspection. The observation from human in predicting the tumour may mislead due to noise and distortions found in the images. This method is impractical for large amount of data and also very time consuming.

So, automated tumour detection methods are developed as it would save radiologist time. The MRI brain tumour detection is complex task due to complexity and variant of tumours. Tumour is identified in brain MRI using Machine Learning algorithms. The proposed work is divided into three sections: Preprocessing steps are applied on the brain MRI images, then texture features are extracted using Gray Level Co-occurrence Matrix (GLCM) and finally classification is performed using machine learning algorithm.

# METHODOLOGY




1. **Business Understanding:** Intention of our project is outlined from a business perspective which aims to successfully classify brain tumour patients using MRI scans.

2. **Data Required:** We require brain MRI scans of patients diagnosed with pituitary tumour as well as some normal scans, we scraped our data from Kaggle (https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumorclassification-mri) under License CC0: Public Domain. And this data represents our problem.

3. **Data Preparation:** Data we are using is much ready to use, for good measures we have resized the images, converted them to suitable dimension arrays, feature scaling and principal component analysis etc before fitting.

4. **Modelling:** Here the data is expressed through apart models to give meaningful insights, new knowledge and patterns. Here we have used Logistic regression as well as support vector machine and then compared their accuracy with svm leading.

5. **Evaluation:** We used. score function of svc and lr to obtain the score for each model.

6. **Deployment:** This tested model is now used on new data outside the scope of dataset, we can now successfully run our model on previously unseen data

# Code and Output

## Importing Modules

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_curve, auc, confusion_matrix
from sklearn.datasets import make_classification
from sklearn.neighbors import KNeighborsClassifier
```

## Collecting Data

In [2]:
```
import os

train_path = r'E:/NSUT/6th Sem/Operating System/os_project/dataset/Training/'
test_path = r'E:/NSUT/6th Sem/Operating System/os_project/dataset/Testing/'

path = os.listdir(train_path)
classes = {'no_tumor':0, 'pituitary_tumor':1}
```

## Resizeing data

In [3]:
```
import cv2
X = []
Y = []
for cls in classes:
    pth = train_path+cls
    for j in os.listdir(pth):
        img = cv2.imread(pth+'/'+j, 0)
        img = cv2.resize(img, (200,200))
        X.append(img)
        Y.append(classes[cls])
```

## Converting data in numeric form

In [4]:
```
X = np.array(X)
Y = np.array(Y)
```

In [5]:
```
# Checking what are the sub arrays in our software. i,e. 0 - No Tummer , 1 - Tumor
np.unique(Y)
```

Out[5]:
```
array([0, 1])
```

In [6]:
```
# Checking total number of sampeles in data set which are having Tummer and No Tummer
pd.Series(Y).value_counts()
```

Out[6]:
```
1    827
0    395
dtype: int64
```

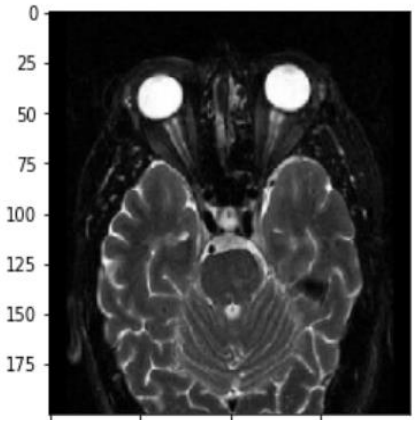
In [7]:
```
# Checking shape - this tells us Total number of samples and dimmention of samples
X.shape
```

Out[7]:
```
(1222, 200, 200)
```

# VISUALISING DATA

In [8]:
```
plt.imshow(X[1], cmap='gray')
```

Out[8]:
```
<matplotlib.image.AxesImage at 0x1458c031e20>
```




# PREPARING DATA

In [9]:
```
# SK Learn works on 2 Dimensional data. But we had 3 Dimensional data above.
# So by reshaping it into 2 dimensional data we can continue
X_updated = X.reshape(len(X), -1)
X_updated.shape
```

Out[9]:
```
(1222, 40000)
```

# Using Train - Test split

In [10]:
```
xtrain, xtest, ytrain, ytest = train_test_split(X_updated, Y, random_state=10,
                                                test_size=.20)
```

In [11]:
```
# 977 sampels for Training the Data
# 245 samples for Testing the Data
xtrain.shape, xtest.shape
```

Out[11]:
```
((977, 40000), (245, 40000))
```

# FEATURE SCALING

In [12]:
```
# We could have also used standard scaler and min max scaler
# But we used Feature scaler because the RGB value of an image ranges from 0-255
# So we devided the samples by 255
# That is why we are getting all outcomes in 0 or 1
print(xtrain.max(), xtrain.min())
print(xtest.max(), xtest.min())
xtrain = xtrain/255
xtest = xtest/255
print(xtrain.max(), xtrain.min())
print(xtest.max(), xtest.min())
```

```
255 0
255 0
1.0 0.0
1.0 0.0
```

In [13]:
```
# Principle Component Analisys (Data reduction algo.)
# reduce number of atributes without significant loss in info.
from sklearn.decomposition import PCA
```

In [14]:
```
print(xtrain.shape, xtest.shape)

pca = PCA(.98)
# pca_train = pca.fit_transform(xtrain)
# pca_test = pca.transform(xtest)
pca_train = xtrain
pca_test = xtest
```

```
(977, 40000) (245, 40000)
```

# Training Model

In [15]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
```

- Logistic Regression

In [16]:
```
# Training Model
# high C means "Trust this training data a lot", while a low value says
#"This data may not be fully representative of the real world data, so if it's telling
#you to make a parameter really large, don't listen to it"
import warnings
warnings.filterwarnings('ignore')
lg = LogisticRegression(C=0.1)
lg.fit(pca_train, ytrain)
```

Out[16]:
```
LogisticRegression(C=0.1)
```

# Training Model

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- Logistic Regression

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lg.fit(pca_train, ytrain)
```

Out[16]:
```
LogisticRegression(C=0.1)
```

- Support Vector Machines

In [17]:
```
sv = SVC()
sv.fit(pca_train, ytrain)
```

Out[17]:
```
SVC()
```

- Random Forest

In [18]:
```
rf = RandomForestClassifier(n_estimators=100, random_state=10)
rf.fit(pca_train, ytrain)
```

Out[18]:
```
RandomForestClassifier(random_state=10)
```

- K Nearest Neighbour

In [19]:
```
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(pca_train, ytrain)
```

Out[19]:
```
KNeighborsClassifier()
```

# Evaluation [Logistic Regression]

In [20]:
```
print("Training Score:", lg.score(pca_train, ytrain))
print("Testing Score:", lg.score(pca_test, ytest))
```

```
Training Score: 1.0
Testing Score: 0.9591836734693877
```

## Evaluation [SVM]

In [21]:
```
print("Training Score:", sv.score(pca_train, ytrain))
print("Testing Score:", sv.score(pca_test, ytest))
```

```
Training Score: 0.9938587512794268
Testing Score: 0.963265306122449
```

## Evaluation [Random Forest Classifier]

In [22]:
```
print("Training Score:", rf.score(pca_train, ytrain))
print("Testing Score:", rf.score(pca_test, ytest))
```

```
Training Score: 1.0
Testing Score: 0.9714285714285714
```

## Evaluation [K-Nearest Neighbors Classifier]

In [23]:
```
print("Training Score:", knn.score(pca_train, ytrain))
print("Testing Score:", knn.score(pca_test, ytest))
```

```
Training Score: 0.9488229273285568
Testing Score: 0.9428571428571428
```

## Deducing the best classifier

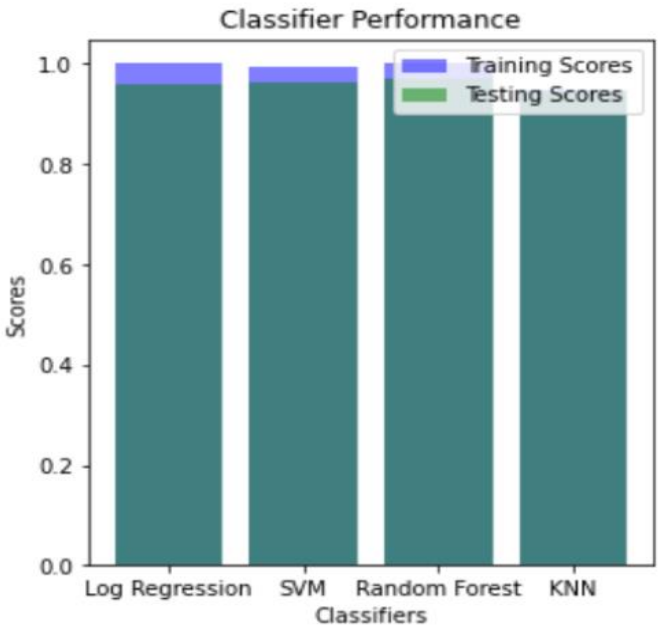
In [24]:
```
classifiers = ['Log Regression', 'SVM', 'Random Forest', 'KNN']
training_scores = [1.0, 0.9938587512794268, 1.0, 0.9488229273285568]
testing_scores = [0.9591836734693877, 0.963265306122449, 0.9714285714285714, 0.9428571428571428]

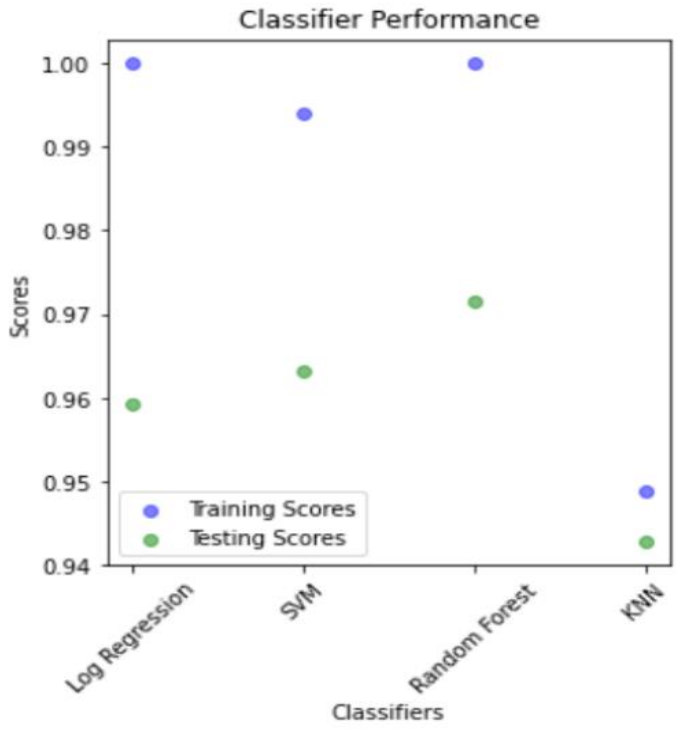
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 5))

x_pos = [i for i, _ in enumerate(classifiers)]
ax1.bar(x_pos, training_scores, color='blue', alpha=0.5, label='Training Scores')
ax1.bar(x_pos, testing_scores, color='green', alpha=0.5, label='Testing Scores')
ax1.set_xlabel('Classifiers')
ax1.set_ylabel('Scores')
ax1.set_title('Classifier Performance')
ax1.set_xticks(x_pos)
ax1.set_xticklabels(classifiers)
ax1.legend()

ax2.scatter(classifiers, training_scores, color='blue', alpha=0.5, label='Training Scores')
ax2.scatter(classifiers, testing_scores, color='green', alpha=0.5, label='Testing Scores')
ax2.set_xlabel('Classifiers')
ax2.set_ylabel('Scores')
ax2.set_title('Classifier Performance')
ax2.tick_params(axis='x', rotation=45)
ax2.legend()

plt.show()
```




- Hence, we can see that **Random Forest** works with greater accuracy than rest here.

# Prediction

In [25]:
```
pred = rf.predict(pca_test)
np.where(ytest!=pred)
```

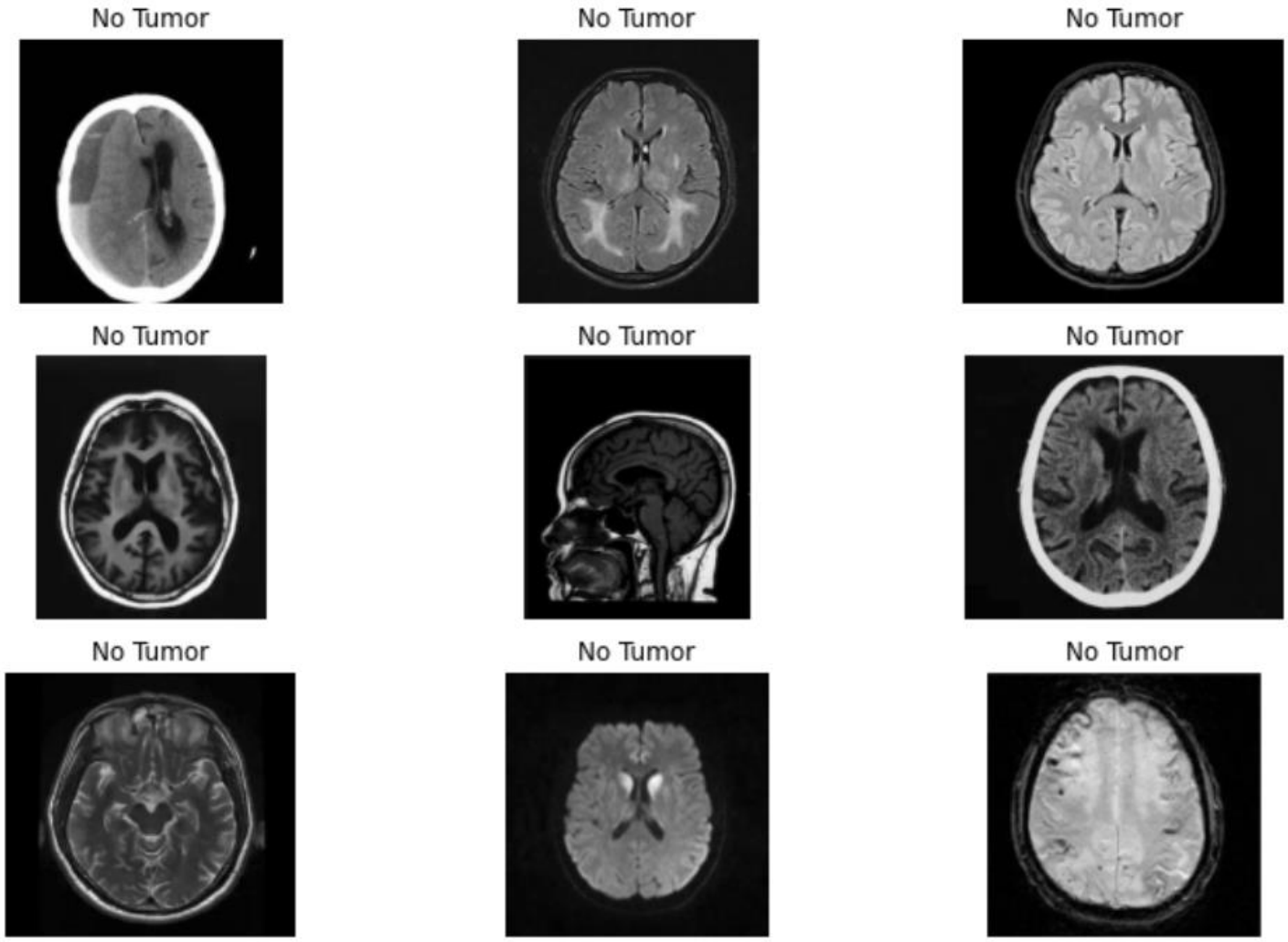
Out[25]:
```
(array([  3,  49, 128, 139, 212, 227, 235], dtype=int64),)
```

# Test Model

In [26]:
```
dec = {0:'No Tumor', 1:'Positive Tumor'}#Classes
```

In [27]:
```
plt.figure(figsize=(12,8))
p = os.listdir(test_path)
c=1
for i in os.listdir(test_path + '/no_tumor')[:9]:
    plt.subplot(3,3,c)

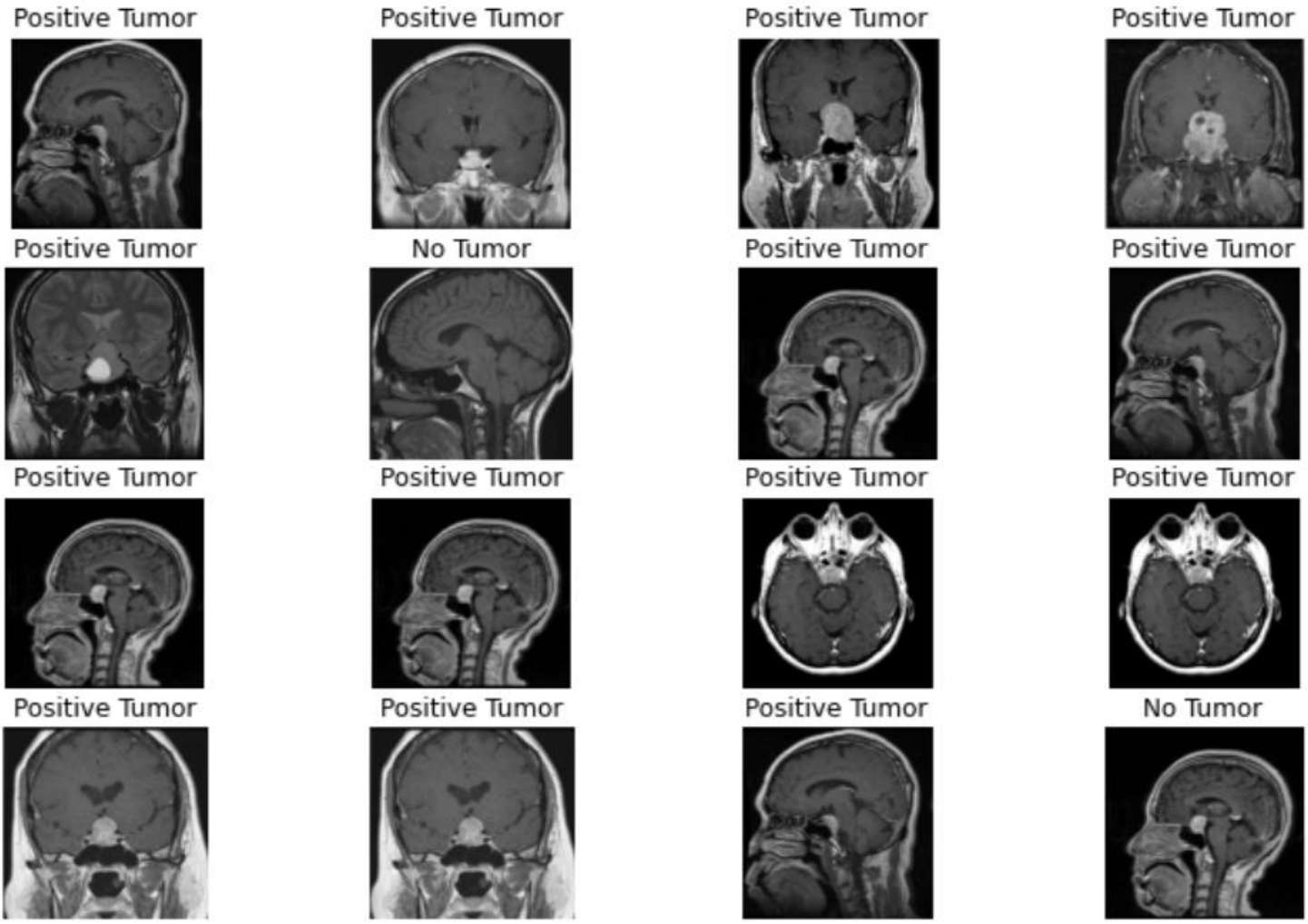
    img = cv2.imread(test_path + '/no_tumor/'+i,0)
    if img is None:
        print('Wrong path:', path)
    else:
        img1 = cv2.resize(img, (200,200))
        img1 = img1.reshape(1,-1)/255
        p = rf.predict(img1)
        plt.title(dec[p[0]])
        plt.imshow(img, cmap='gray')
        plt.axis('off')
        c+=1
```




In [28]:

```
plt.figure(figsize=(12,8))
p = os.listdir(test_path)
c=1
for i in os.listdir(test_path + 'pituitary_tumor')[:16]:
    plt.subplot(4,4,c)

    img = cv2.imread(test_path + 'pituitary_tumor/'+i,0)
    img1 = cv2.resize(img, (200,200))
    img1 = img1.reshape(1,-1)/255
    p = rf.predict(img1)
    plt.title(dec[p[0]])
    plt.imshow(img, cmap='gray')
    plt.axis('off')
    c+=1
```

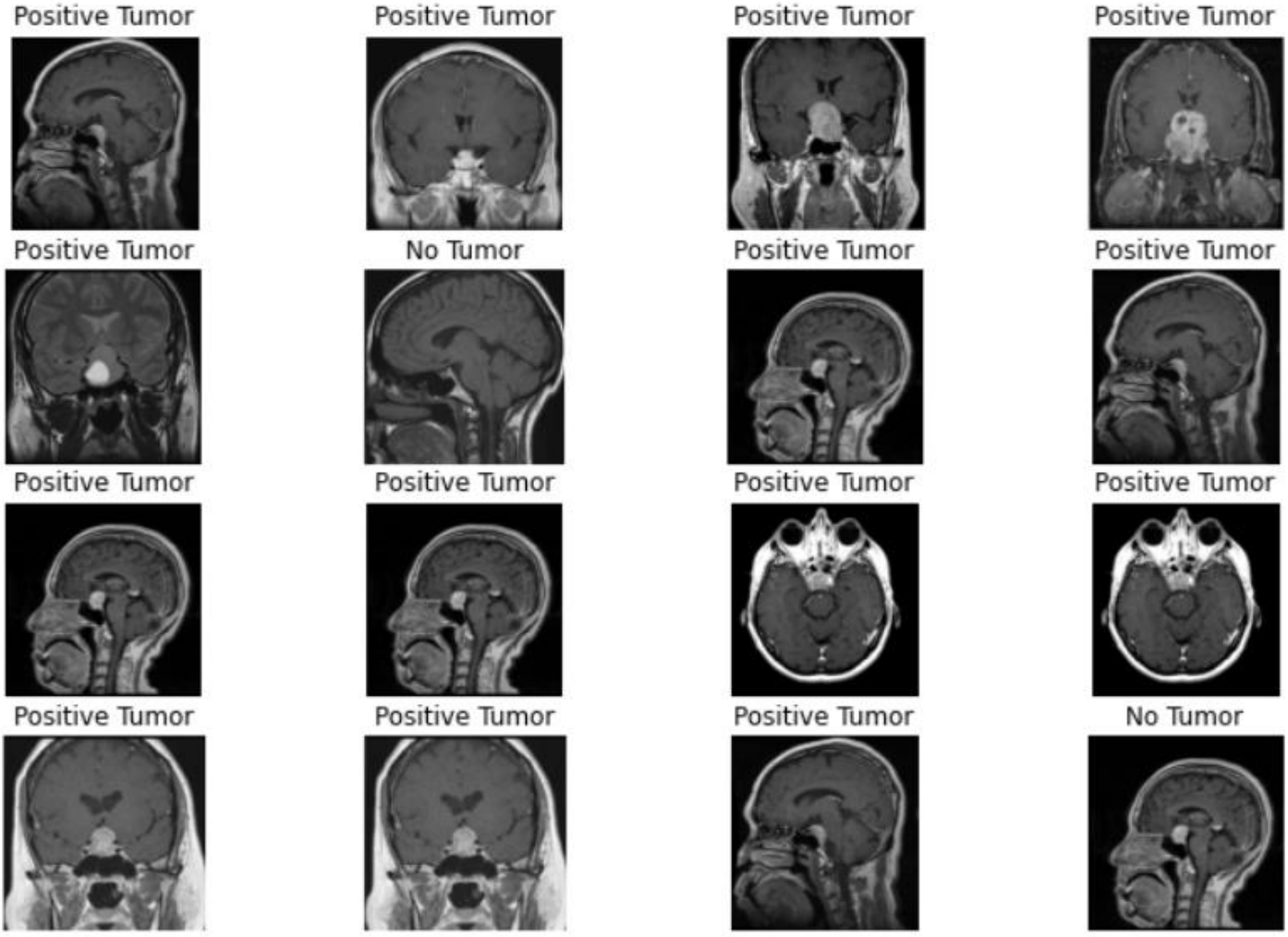

Positive Tumor
Positive Tumor
Positive Tumor
Positive Tumor
Positive Tumor
No Tumor
Positive Tumor
Positive Tumor
Positive Tumor
Positive Tumor
Positive Tumor
Positive Tumor
Positive Tumor
Positive Tumor
Positive Tumor
No Tumor

---X---X---X--

# RESULTS

## Brain Tumours very successfully detected:

With little to no false negatives

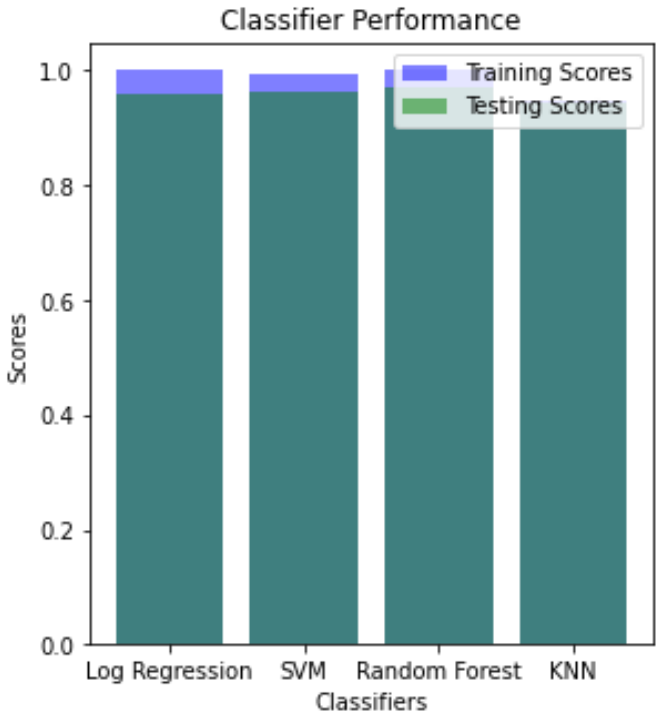


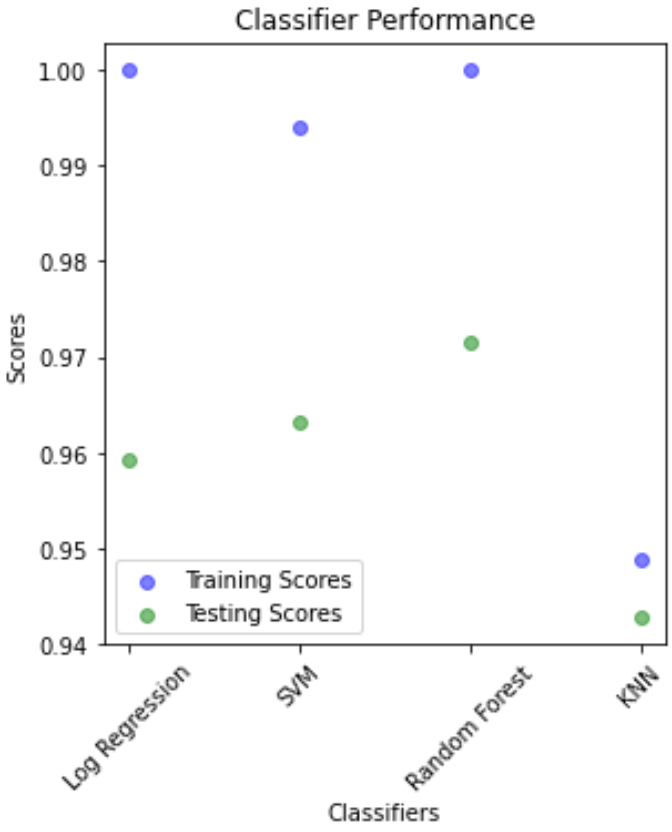
# Conclusion

We used the following classifiers from SciKitLearn library of python to conclude our project:

1. Logistic Regression
2. Support Vector Machine
3. Random Forest
4. K-Nearest Neighbour

Following depicts their respective test and train scores :-




Hence, we concluded **Random Forest** to be the best classifier and carried our project with it.

```
Training Score: 1.0
Testing Score: 0.9714285714285714
```

# References


Youtube: https://www.youtube.com/watch?v=5lgrlddp-98

Kaggle: https://www.youtube.com/redirect?event=video_description&redir_token=QUFFLUhqbXFBcFVndU1nM05QUEJ5UHVTMmxjWEZuUHF5QXxBQ3Jtc0trUXdiTUhOS1JjbORVNmpPdlpnLTh1bTI2ZnVIaFB1LXJac1huYkUyR19YMEJvUVFNLXNWbC1sUWRSTTBYQ1RRTnY4MlVGRWR2V1V2VkU3N01QZjI5UzRPd0JyaVR4emZoMGdQOXUyaURMVWt0SjhCWQ&q=https%3A%2F%2Fwww.kaggle.com%2Fsartajbhuvaji%2Fbrain-tumor-classification-mri&v=5lgrlddp-98

Geeks for Geeks: https://www.geeksforgeeks.org/tumor-detection-using-classification-machine-learning-and-python/?ref=gcse