



## BRAIN TUMOR MEDICAL ANALYSIS USING DEEP LEARNING

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### ABSTRACT

The primary regulator of the humanoid system is the human brain. A brain tumour develops when brain cells grow and divide abnormally, and brain cancer develops when brain tumours continue to grow. Computer vision is important in the field of human health because it eliminates the need for human judgement to produce correct results. The most dependable and secure imaging techniques for magnetic resonance imaging (MRI) are CT scans, X-rays, and MRI scans. MRI can identify minute items. Our paper will concentrate on the many methods for using brain MRI to find brain cancer. In this research, To remove the noises contained in an MR picture, we pre-processed the data using the bilateral filter (BF). For accurate tumour region detection, this was followed by the binary thresholding and Convolution Neural Network (UNET) segmentation techniques. Datasets for training, testing, and validation are used. We shall determine whether the subject has a brain tumour based on our machine. Accuracy, sensitivity, and specificity are just a few of the performance indicators that will be used to analyse the final results. It is hoped that the planned work will perform more admirably than its competitors.

**KEYWORDS:** Brain tumor, Magnetic resonance imaging, Adaptive Bilateral Filter, Convolution Neural Network.

### 1 INTRODUCTION

Medical imaging is the method and procedure used to provide visual depictions of a body's interior for use in clinical analysis and medical intervention, as well as to show how certain organs or tissues work. Medical imaging aims to identify and cure disease as well as disclose internal structures that are covered by the skin and bones. In order to detect anomalies, medical imaging also creates a database of typical anatomy and physiology.

The handling of images with a computer is referred to as medical imaging processing. This processing entails a wide



range of methods and actions, including image acquisition, archiving, presentation, and communication. This procedure aims to manage and identify disorders. Through this approach, a database of the typical organ anatomy and function is created, making it simple to spot irregularities. This procedure involves both organic and radiological imaging, which makes use of magnetic scopes, solo grapy, thermal, and isotope imaging, as well as electromagnetic energy (X-rays and gamma rays). The location and operation of the body are recorded using a variety of various technologies. Those methods are significantly more constrained than the modulates that result in images. Using a computer to edit a digital image is known as an image processing technique. This method has a lot of advantages, including flexibility, adaptability, data storage, and communication. The development of numerous image scaling algorithms has made it possible to maintain photos effectively. This method requires numerous sets of criteria to be applied concurrently to the images. One of the most prevalent and deadly brain disorders that has impacted and destroyed many lives around the world is the brain tumour. Cancer is a condition when cancer cells grow in the tissues of the brain. According to a recent cancer study, more than a lakh people receive a diagnosis of a brain tumour each year. Despite consistent efforts to deal with brain tumour consequences, statistics demonstrate unfavourable outcomes for tumour patients. To counter this, researchers are focusing on computer vision to better comprehend the early stages of tumours and how to treat them with cutting-edge therapies.

The two most common procedures to determine the presence of a tumour and pinpoint its location for further treatment choices are magnetic resonance imaging (MR imaging) and computed tomography (CT) scans of the brain. Due to its portability and greater capacity to provide high-definition images of diseased tissues, these two scans are still employed often. There are currently a number of other treatments available for tumours, including chemotherapy, radiation therapy, and surgery. The choice of treatment depends on a number of variables, including the tumor's size, kind, and grade as seen in the MR imaging. It is also responsible for determining whether cancer has spread to other body parts.

To optimise therapy operations and reduce diagnostic errors, precise identification of the type of brain disorder is crucial. Through the use of computer-aided diagnostic (CAD) systems, the precision is frequently rudimentary. The main goal of computer vision is to create an accurate output, such as an association estimation, that can help clinicians analyse images more quickly. These developments improve the consistency and accuracy of medical diagnosis, however segmenting an MR picture of the tumour and its area remains a challenging task. Another challenge that makes computerised brain tumour detection and segmentation challenging is the appearance of tumours in specific positions within the brain image without differentiating picture intensities.

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The most popular method for detecting brain tumours and locating their location is magnetic resonance imaging (MRI). In contrast to other approaches, the traditional method for classifying and identifying tumour cells in CT and MR images continues to be highly endorsed for human assessment. The main reasons why MR pictures are used are because they are non-destructive and non-ionizing. High-definition images provided by MR imaging are frequently used to find brain tumours. Different MRI schemes exist, including flair, T1-weighted, and T2-weighted images. There are numerous methods for processing images, including pre-processing, image segmentation, image enhancement, feature extraction, and classifiers.



## 2. LITERATURE SURVEY AND RELATED WORK

The most popular method for detecting brain tumours and locating their location is magnetic resonance imaging (MRI). In contrast to other approaches, the traditional method for classifying and identifying tumour cells in CT and MR images continues to be highly endorsed for human assessment. The main reasons why MR pictures are used are because they are non-destructive and non-ionizing. High-definition images provided by MR imaging are frequently used to find brain tumours. Different MRI schemes exist, including flair, T1-weighted, and T2-weighted images. There are numerous methods for processing images, including pre-processing, image segmentation, image enhancement, feature extraction, and classifiers.

We give a brief overview of the various clustering strategies that have been put forth from 2002 to 2018 in the literature survey. We have read 25 papers, each of which takes a different method to segmentation in one or more parameters. The papers are each summarised in the sections that follow.

- 1 Sivaramakrishnan And Dr. M. Karnan "A Novel Based Approach for Extraction Of Brain Tumor In MRI Images Using Soft Computing Techniques," International Journal Of Advanced Research In Computer And Communication Engineering, Vol. 2, Issue 4, April 2013, Using the Fuzzy C- approach grouping algorithm and histogram equalisation, Sivaramakrishnan (2013) projected an effective and creative finding of the brain tumour location from a picture. Using primary factor assessment to lower the size of the wavelet coefficient allows for the disintegration of images. The predicted FCM clustering technique successfully removed the tumour from the MR images.
- 2 AsraAslam, Ekram Khan, M.M. Sufyan Beg, Improved Edge Detection Algorithm for Brain Tumor Segmentation, Procardia Computer Science, Volume 58,2015, Pp. 430-437, ISSN 1877-0509, For the purpose of segmenting brain tumours, M. M. Sufyan has given a detection method that heavily relied on Sobel feature detection. Their work here links the binary thresholding operation to the Sobel technique and uses a safe contour process to excavate various extents. Following the completion of that procedure, cancer cells are removed using intensity values from the resulting image.
- 3 B.Sathya and R.Manavalan, Image Segmentation by Clustering Methods: Performance Analysis, International Journal of Computer Applications (0975 – 8887) Volume 29– No.11, September 2011, Different clustering techniques, including K-means, Improvised K-means, C-means, and improvised C-means algorithms, were offered by Sathyaetal. (2011). In their study, they described an experimental analysis for sizable datasets made up of original photos. They conducted multiple parametric tests on the found effects before analysing them.
- 4 To locate and contain the fully hysterical region among the aberrant tissues, K. Sudharanietal applied a K-nearest neighbour method to the MR images. Although the process for the suggested work is slow, it provides beautiful results. The sample training step is what determines accuracy.



- 5 Artificial neural networks were used in a model that Dalia Mahmoudetal demonstrated to identify tumours in brain scans. They used Artificial Neural Networks to build a computerised recognition system for MR imaging. When the Elman community was incorporated into the recognition system, it was found that the period of time and accuracy level were high when compared to other ANNs systems. The sigmoid property of this neural community increased the level of tumour segmentation accuracy.
- 6 The proposed work by Mukambikaetal represents a comparative analysis of the Level set technique, discrete wavelength transformations (DWT), and K-method segmentation methods utilised for tumour detection from MR images.

### 3 Implementation Study

#### IMAGE PREPROCESSING AND IMAGE ENHANCEMENT

##### 3.1 .Image Preprocessing:

From Kaggle, the Brain MRI image dataset has been downloaded. Around 1900 MRI pictures, including benign, malignant, and normal ones, are included in the MRIdataset. These MRI scans are used as the first step's input. A crucial and first step in raising the calibre of the brain MRI image is pre-processing. The elimination of impulsive sounds and image scaling are crucial pre-processing stages. The brain MRI image is first transformed into a similar gray-scale image in the initial stage.

##### 3.2 IMAGE PURCHASE FROM DATABASE:

Taking an image from a dataset and processing it is how image acquisition is done in image processing. It is the first step in the workflow sequence because processing cannot take place without an image.

##### 3.3 FROM ONE COLOUR SPACE TO ANOTHER, CONVERT THE IMAGE:

OpenCV offers more than 150 different color-space conversion techniques. The function `cv2.cvtColor(input_image, flag)` is used to convert an image's colour, and flag specifies the conversion method. In our job, we transform the original image into a grayscale version.

##### 3.4 FILTERS:

Filters are mostly employed in image processing to reduce the high frequencies in the image.

##### 3.5 AVERAGE FILTER:

It is a non-linear filtering method for reducing image noise. It is done by numerically ordering all of the window's pixel values, after which the pixel under consideration is swapped out for the median value. Through the 'ON' and 'OFF' of pixels by white, this filter eliminates the salt and pepper noise and the speckle noise.

##### 3.6 IMAGE SEGMENTATION USING BINARY THRESHOLD:

Image segmentation is a method for dividing an image into various components. The main goal of this division is to keep the quality of the photographs while making it simple to analyse and interpret them. The edges of the objects in the photos are also traced using this method. The pixels are labelled using this method based on their properties and intensity. These



pieces take on the qualities of the complete original image, including intensity and resemblance. The body's contours are created using the image segmentation technique for clinical purposes. Machine perception, analysis of malignant diseases, tissue volumes, anatomical and functional studies, visualisation of virtual reality, anomaly analysis, and object definition and detection all require segmentation.

In order to analyse the size, volume, position, texture, and shape of the extracted image, segmentation methods are important since they have the ability to discover or identify the anomalous component from the image. By maintaining the threshold information during MR image segmentation, it is possible to more precisely detect the damaged regions. The idea that objects placed near together might have similar properties and features was formerly considered fashionable.

### 3.7 BRAIN TUMOR CLASSIFICATION USING CONVOLUTION NEURAL NETWORK

The greatest methods for identifying images, including any type of medical imaging, are classification. Each and every algorithm for classifying objects is based on the assumption that an image contains one or more characteristics and that each of these features belongs to a particular class.

Convolutional Neural Network (CNN) will be employed as an automatic and trustworthy classification method because of its resilient structure, which aids in identifying even the smallest details. A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning system that can analyse an input image, rank various features and objects within the image, and distinguish between them. Comparatively speaking, a ConvNet requires substantially less pre-processing than other classification techniques. ConvNet can learn these filters/characteristics with adequate training, whereas in basic approaches filters are hand-engineered.

Through the use of pertinent filters, a ConvNet may effectively capture the spatial and temporal dependencies in a picture. Because there are fewer factors to consider and the weights can be reused, the architecture provides a better fitting to the picture dataset. In other words, the network may be trained to better comprehend the level of complexity in the image. The ConvNet's job is to condense the images into a format that is simpler to analyse without sacrificing elements that are essential for obtaining an accurate forecast.

### 3.8 SEQUENTIAL:

We make an object of the Sequential type to start the neural network.

### 3.9 POOLING:

The spatial size of the convolved feature is minimised by the Pooling layer. Through dimensionality reduction, the amount of computing power needed to process the data will be reduced. Furthermore, it aids in properly training the model by allowing the extraction of dominating characteristics that are rotational and positional invariant.

### 3.10 PREPOCESSING DATA

Pre-processing data is a method for transforming unclean data into a clean dataset. The data was collected from several sources in raw format, making analysis impractical. This method requires pre-processing in 4 easy-to-follow but efficient steps.

- Attribute choice
- Filling out missing values
- Test and training data
- Scaling of features

## 4 PROPOSED WORK

The most extensively studied machine learning algorithms for medical image processing at the moment are CNNs. This is due to the fact that while altering input images, CNNs maintain spatial relationships. As previously indicated, spatial relationships play a critical role in radiography, for instance, in how a bone's edge connects with a muscle or where healthy lung tissue meets malignant tissue. As seen in Fig. 2, a CNN transforms an input image made up of raw pixels using convolutional layers, RELU layers, and pooling layers. The input is then categorised into the class with the highest likelihood using the yearly Fully Connected Layer, which provides class scores or probabilities.

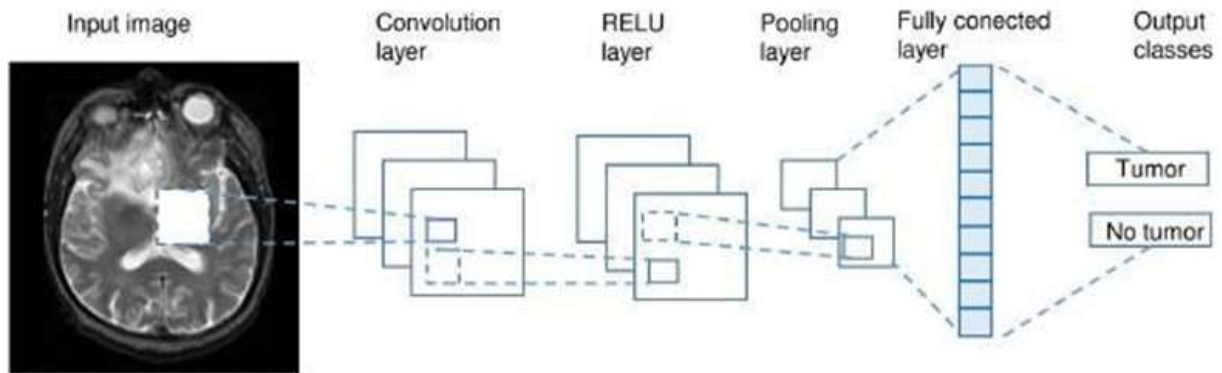


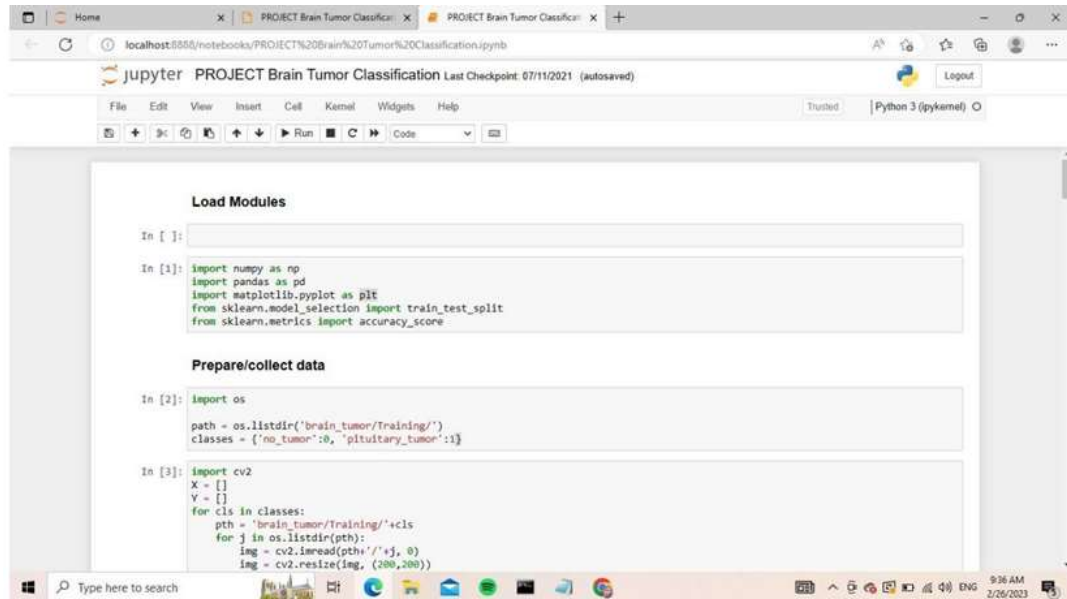
Fig-1: Proposed System.

It is important to research detection, also known as computer-aided detection (CAD), because failing to pick up a lesion on a scan might have serious repercussions for both the patient and the doctor. The 2017 Kaggle Data Science Bowl task required finding malignant lung nodules on CT scans of the lungs. The competition's 2000 CT scans were made available, and Fang Zhou won with a logarithmic loss score of 0.399.

In order to isolate local patches for nodule detection, their technique utilised a 3-D CNN inspired by U-Net architecture. This output was then used to classify the likelihood of cancer in a second stage with two fully connected layers. Shantel tested the ability of well-known CNN architectures to identify interstitial lung illness and thoracic abdominal lymph nodes on CT imaging. It is crucial to find lymph nodes since they may be a sign of an infection or malignancy. Using Google Net, they were able to detect mediastinal lymph nodes with an AUC score of 0.95 and an 85% sensitivity, which was cutting edge.

Additionally, they provided evidence for the advantages of transfer learning and the usage of up to 22-layer deep learning architectures as opposed to the typical fewer layers used in medical picture analysis. The CNN pre-trained on natural pictures algorithm overcame feat to win the 2013 ILSVRC localization task. Ciompietal. used over task to forecast the existence of nodules inside and around longspurs on 2-dimensional slices of CT lung scans orientated in the coronal, axial, and sagittal planes. They used this strategy with straightforward SVM and RF binary classifiers, as well as their own innovative 3-dimensional descriptor, the Bag of Frequencies.

## 5 RESULTS AND DISCUSSION SCREENSHOTS



```
Load Modules

In [ ]:

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

Prepare/collect data

In [2]: import os
path = os.listdir('brain_tumor/Training/')
classes = {'no_tumor':0, 'pituitary_tumor':1}

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

Fig-2: Importing modules

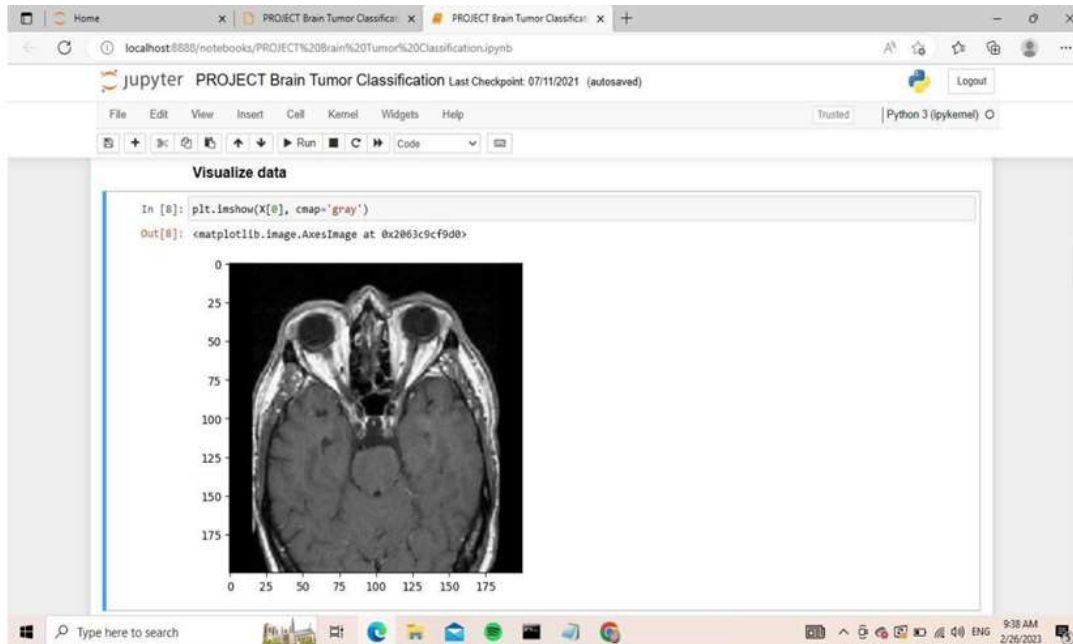
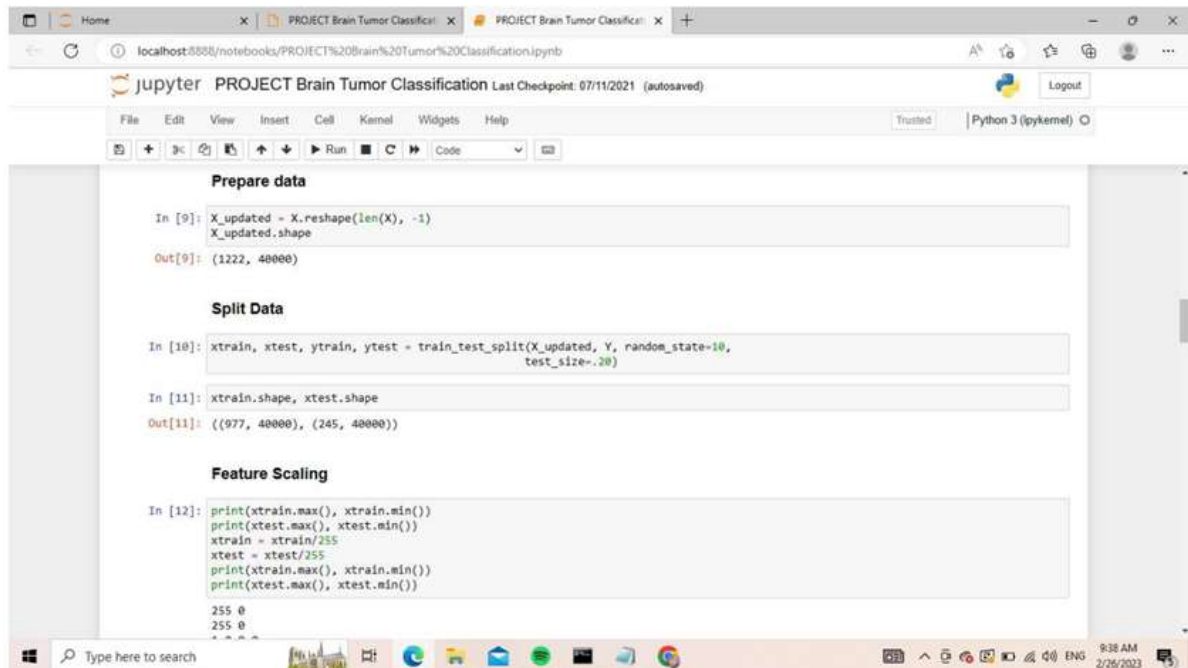


Fig-3: visualize data



```

Prepare data

In [9]: X_updated = X.reshape(len(X), -1)
X_updated.shape
Out[9]: (1222, 40000)

Split Data

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

In [11]: xtrain.shape, xtest.shape
Out[11]: ((977, 40000), (245, 40000))

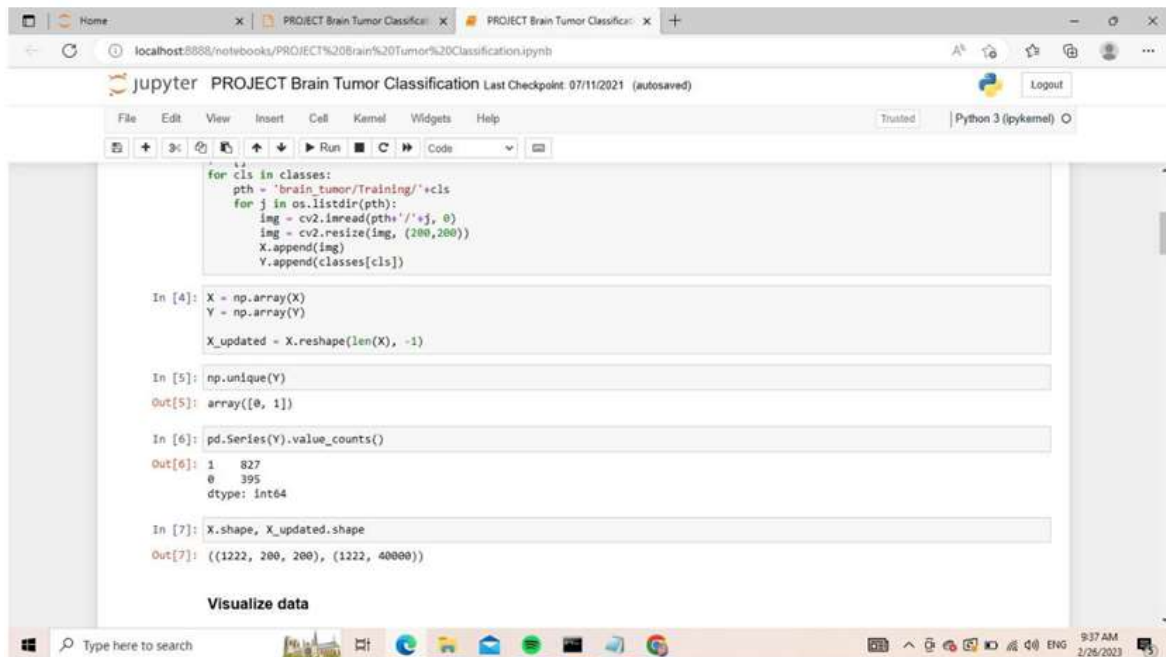
Feature Scaling

In [12]: 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

```

Fig-4: preparing, splitting data



```

for cls in classes:
    pth = 'brain_tumor/Training/'+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])

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

X_updated = X.reshape(len(X), -1)

In [5]: np.unique(Y)
Out[5]: array([0, 1])

In [6]: pd.Series(Y).value_counts()
Out[6]: 1    827
0    395
dtype: int64

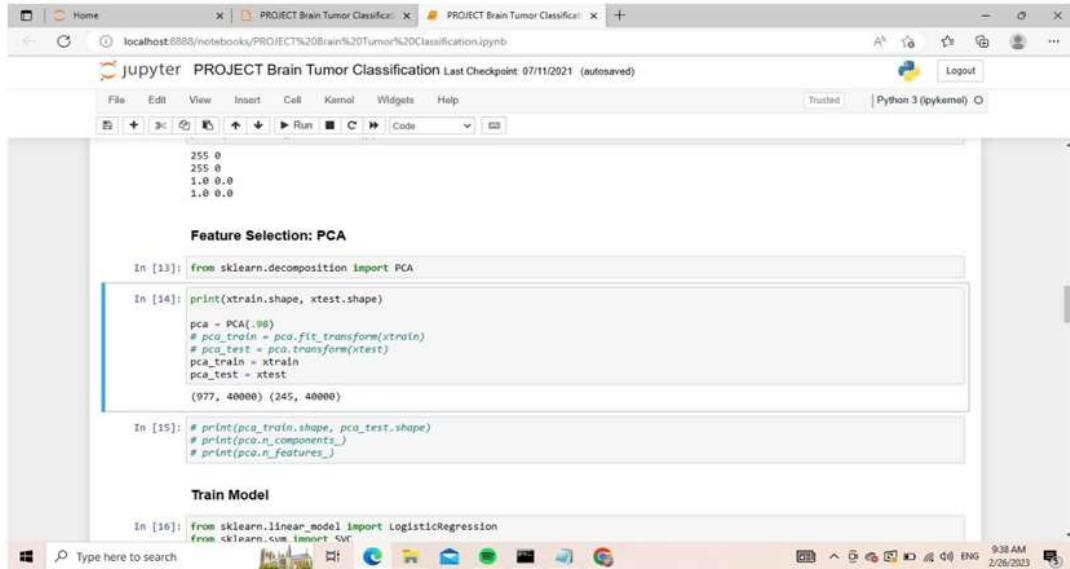
In [7]: X.shape, X_updated.shape
Out[7]: ((1222, 200, 200), (1222, 40000))

Visualize data

```

Fig-5: Displaying shapes of X and Y





```
255 0
255 0
1.0 0.0
1.0 0.0

Feature Selection: PCA

In [13]: from sklearn.decomposition import PCA

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

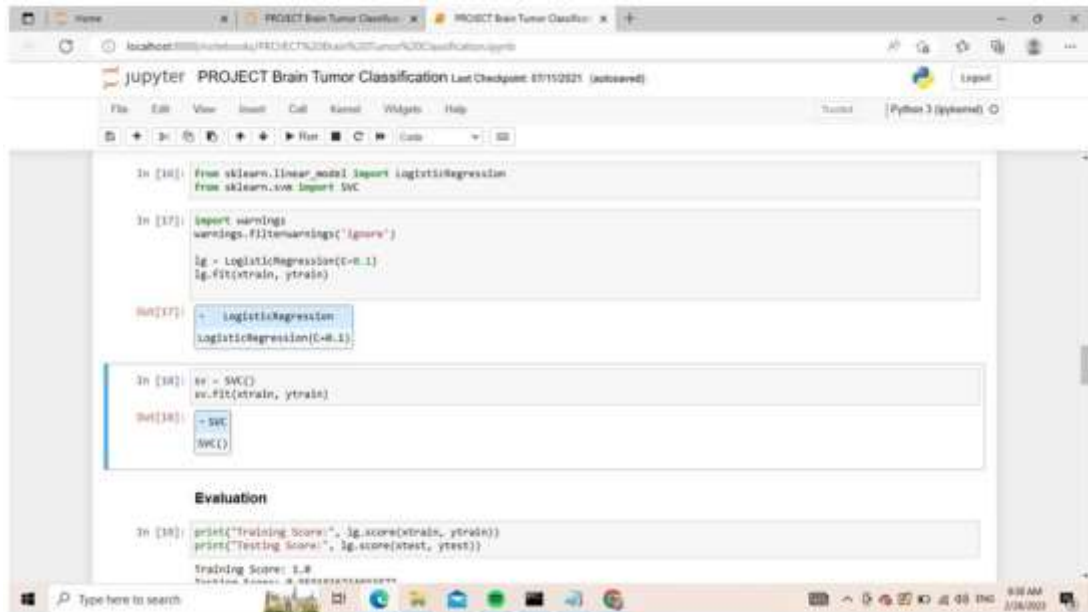
pca = PCA(.98)
# pca_train = pca.fit_transform(xtrain)
# pca_test = pca.transform(xtest)
pca_train = xtrain
pca_test = xtest
(977, 40000) (245, 40000)

In [15]: # print(pca_train.shape, pca_test.shape)
# print(pca.n_components_)
# print(pca.n_features_)

Train Model

In [16]: from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
```

Fig-6: Feature selection



```
In [16]: from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC

In [17]: import warnings
warnings.filterwarnings('ignore')
lg = LogisticRegression(C=0.1)
lg.fit(xtrain, ytrain)

Out[17]: LogisticRegression
LogisticRegression(C=0.1)

In [18]: sv = SVC()
sv.fit(xtrain, ytrain)

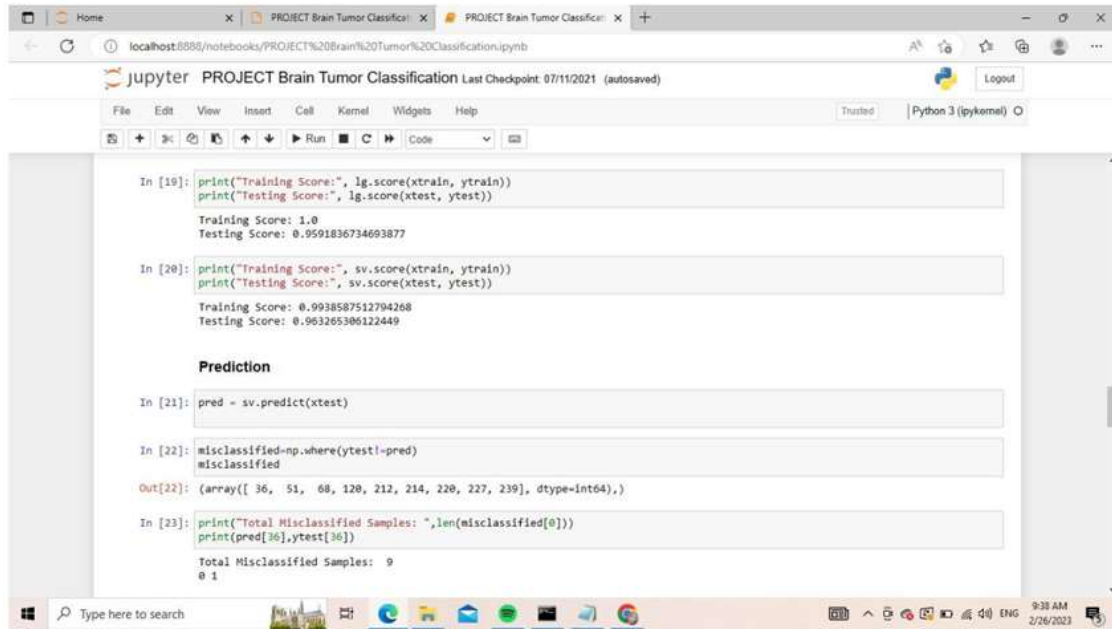
Out[18]: SVC
SVC()

Evaluation

In [19]: print("Training Score:", lg.score(xtrain, ytrain))
print("Testing Score:", lg.score(xtest, ytest))

Training Score: 0.8
Testing Score: 0.8888888888888888
```

Fig-7: Perform Logistic regression and SVM



```
In [10]: print("Training Score:", lg.score(xtrain, ytrain))
print("Testing Score:", lg.score(xtest, ytest))
Training Score: 1.0
Testing Score: 0.9591836734693877

In [20]: print("Training Score:", sv.score(xtrain, ytrain))
print("Testing Score:", sv.score(xtest, ytest))
Training Score: 0.9938587512794268
Testing Score: 0.963265306122449

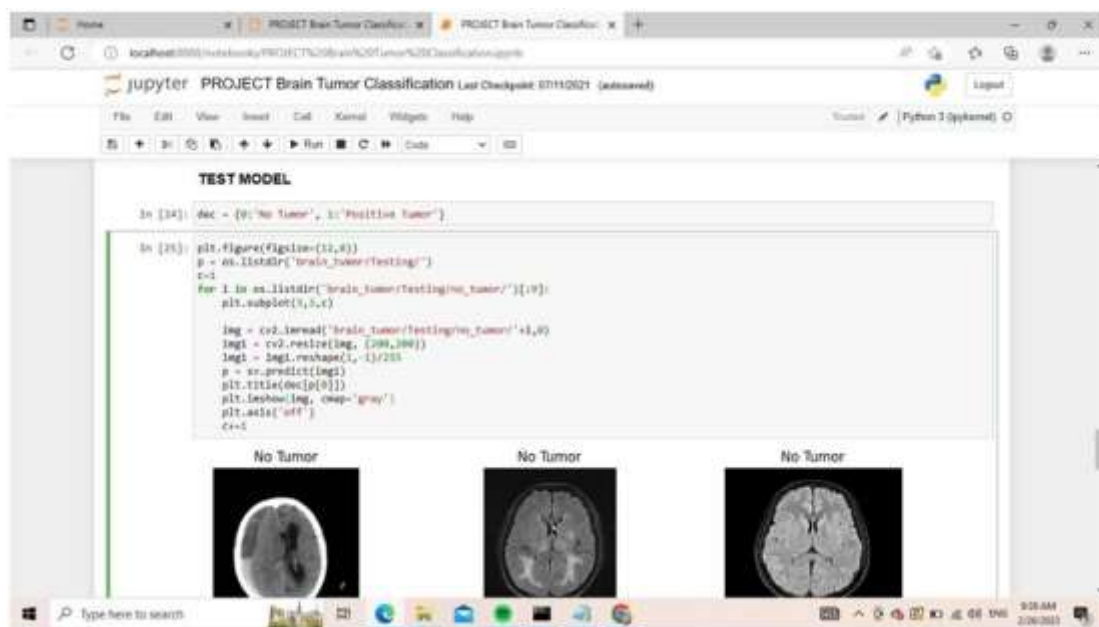
Prediction

In [21]: pred = sv.predict(xtest)

In [22]: misclassified=np.where(ytest!=pred)
misclassified
Out[22]: (array([ 36,  51,  68, 120, 212, 214, 220, 227, 239]),)

In [23]: print("Total Misclassified Samples: ",len(misclassified[0]))
print(pred[36],ytest[36])
Total Misclassified Samples: 9
0 1
```

Fig-8: Prediction



```
TEST MODEL

In [24]: dec = (0: 'No Tumor', 1: 'Positive Tumor')

In [25]: plt.figure(figsize=(12,8))
p = os.listdir('brain_tumor/testing')
c=1
for i in os.listdir('brain_tumor/testing/no_tumor/')[19]:
    plt.subplot(3,3,c)

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

No Tumor      No Tumor      No Tumor


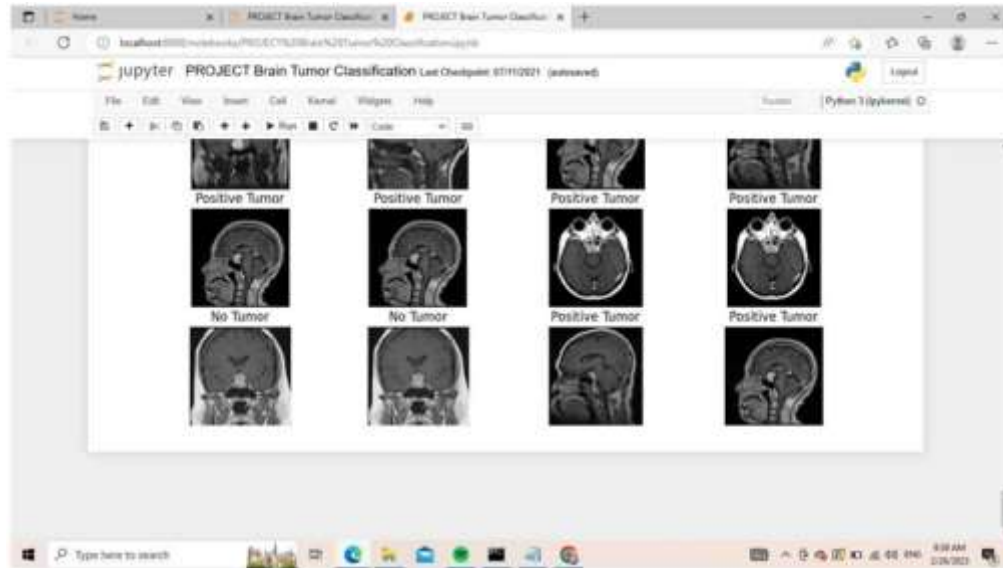


Fig-9: Testing module



**Fig-10: Displaying different types of tumors.**

## 6 CONCLUSION AND FUTURE WORK

Using the Convolution Neural Network, we suggested a computerised technique for the segmentation and identification of a brain tumour. Using the file location, the input MR pictures are read from the local device and transformed into grayscale images. To remove noises from the raw photos, these images are pre-processed using an adaptive bilateral filtering algorithm. Convolution Neural Network segmentation and binary thresholding are performed to the denoised picture to identify the tumour region in the MR images. The suggested model delivers promising results without any errors and takes a great deal less computing time, with an accuracy of 84%.

Experimentation reveals that the suggested method requires a sizable training dataset for more accurate results; in the field of medical image processing, collecting medical data is a laborious task, and in certain rare instances, the datasets could not be available. In each of these scenarios, the suggested method must be trustworthy enough to reliably identify tumour locations from MR images. The suggested method can be further improved by working with weakly trained algorithms that can detect irregularities with little or no training data. Self-learning algorithms would also help to improve algorithm accuracy and speed up processing.

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