



AUTOMATED BRAIN TUMOR DIAGNOSIS THROUGH DEEP LEARNING TECHNIQUES

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ABSTRACT

The human brain is the main regulator of the humanoid system. When brain cells grow and divide improperly, a brain tumour forms; when brain tumours keep growing, brain cancer results. Because computer vision produces accurate results without requiring human judgment, it is significant in the realm of human health. CT, X-ray, and MRI scans are the most reliable and secure imaging methods for magnetic resonance imaging (MRI). An MRI can detect little objects. The many techniques for utilizing brain MRI to detect brain cancer will be the main focus of our paper. In this study, we used the bilateral filter (BF) to pre-process the data in order to eliminate the noise from an MR image. This was followed by the binary thresholding and Convolution Neural Network (UNET) segmentation approaches for precise tumor region detection. There are datasets used for validation, testing, and training. Using our gadget, we will ascertain whether the patient has a brain tumor. A number of performance metrics, including sensitivity, specificity, and accuracy, will be employed in the analysis of the end product. It is intended that the proposed work will outperform its rivals.

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

1 INTRODUCTION

Medical imaging is the process and method used to display how certain organs or tissues function as well as to provide visual representations of the inside of the body for use in clinical analysis and medical intervention. The goals of medical imaging are to reveal internal structures hidden by the skin and bones as well as to diagnose and treat diseases. Medical imaging also builds a database of normal anatomy and physiology to identify anomalies.

Medical imaging processing is the term used to describe image processing done by a computer. Several techniques and procedures are involved in this processing, such as image capture, archiving, presenting, and communicating. The goal of this process is to recognize



and treat disorders. By using this method, a database of the structure and function of typical organs is produced, which makes it easy to identify abnormalities. Using magnetic scopes, solitary grapy, thermal, isotope, and electromagnetic energy (X-rays and gamma rays), this process combines radiological and organic imaging. Numerous technologies are used to record the body's location and functions. Compared to modulates that produce images, those techniques are much more limited. An image processing technique is the process of altering a digital image with a computer. Numerous benefits come with this technology, including connection, data storage, versatility, and adaptability. Several image scaling techniques have been developed, which has allowed for efficient photo maintenance. Several sets of criteria must be applied to the photos simultaneously in order to use this strategy. Brain tumors are among the most common and devastating brain conditions that have affected and destroyed countless lives worldwide. When cancer cells proliferate in the brain's tissues, the illness is known as cancer. A recent cancer study found that every year over a lakh patients are diagnosed with brain tumours. Statistics show that patients with brain tumors do not always have the best outcome, even with continuous attempts to address their effects. In response, scientists are concentrating on computer vision in order to gain a better understanding of the early phases of tumors and how to treat them with state-of-the-art medications.

The two most popular methods for identifying whether a tumor exists and locating it so that additional treatment options can be considered are brain computed tomography (CT) scans and magnetic resonance imaging (MR imaging). These two scans are still often used because of their mobility and their ability to produce high-definition images of sick tissues. Currently, chemotherapy, radiation therapy, and surgery are among the numerous treatments available for tumors. The size, nature, and grade of the tumor as revealed by MR imaging are among the factors that influence the treatment decision. It is also in charge of figuring out whether cancer has moved to different areas of the body.

Accurately identifying the type of brain illness is essential for optimizing therapeutic outcomes and minimizing diagnostic mistakes. The accuracy is often basic due to the usage of computer-aided diagnostic (CAD) technologies. The primary objective of computer vision is to produce an accurate output that can speed up the analysis of images by physicians, such as an association estimation. Although these advancements increase the reliability and precision of medical diagnoses, it is still difficult to separate an MR image of a tumor and its surrounding tissue. The emergence of tumors in certain locations within the brain imaging without differing picture intensities is another difficulty for computerised brain tumour identification and segmentation.

due to their portability and ability to capture detailed images of infected tissues. Currently, chemotherapy, radiation therapy, and surgery are among the numerous treatments available for tumors. The size, nature, and grade of the tumor as revealed by MR imaging are among the factors that influence the treatment decision. It is also responsible for assessing whether cancer has progressed to other areas of the body.

Accurately identifying the type of brain illness is essential for optimizing therapeutic outcomes and minimizing diagnostic mistakes. The accuracy is often basic due to the usage of computer-aided diagnostic (CAD) technologies. The primary objective of computer vision is to produce an accurate output that can speed up the analysis of images by physicians, such



as an association estimation. Although these advancements increase the reliability and precision of medical diagnoses, it is still difficult to separate an MR image of a tumor and its surrounding tissue. The emergence of tumors in specific areas within the brain image without different picture intensities presents another challenge that makes automated detection of brain tumours and segmentation by diagnostic imaging modalities like CT scan and MRI a challenging operation. Both modalities offer benefits in terms of detection, depending on the kind of place and inspection objective.

Magnetic resonance imaging is the most widely used technique for identifying brain tumors and pinpointing their location (MRI). Unlike other strategies, the conventional method is still strongly recommended for use in human evaluation when it comes to classifying and recognizing tumor cells in CT and MR images. The primary applications for magnetic resonance imaging (MR) stem from its non-destructive and non-ionizing properties. Finding brain tumors is often aided by the high-definition images produced by magnetic resonance imaging. There are several MRI schemes, including as T1-weighted, T2-weighted, and flair pictures. Image processing can be done in many different ways, such as feature extraction, classifiers, pre-processing, image segmentation, and image enhancement.

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 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, Improved K-means, C-means, and improved C-means algorithms, were offered by Sathya et al. (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. Sudharani et al 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 Mahmoud et al 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 Mukambika et al 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

.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 MRI dataset. 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.

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.

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.

FILTERS:

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

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.

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.

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.

SEQUENTIAL:

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

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.

PREPOSSESSING 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

4PROPOSED 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.

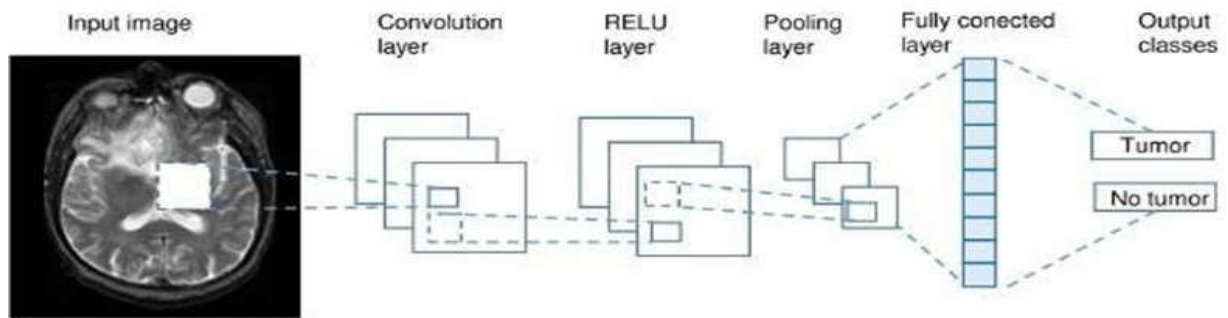


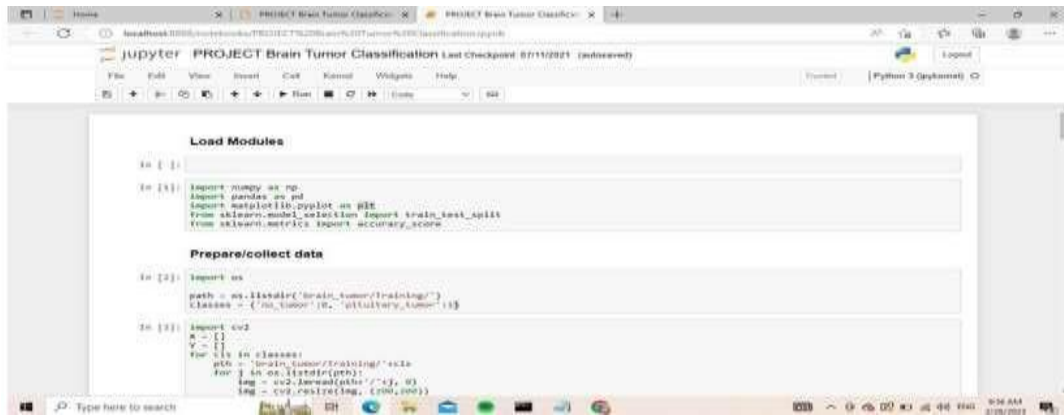
Fig-1: Proposed System.

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 [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', 'glioma_tumor')

In [3]:
import cv2
X = []
Y = []
for i in classes:
    path = 'brain_tumor/training/'+i+ '/'
    for j in os.listdir(path):
        img = cv2.imread(path+'j', 0)
        img = cv2.resize(img, (100,100))
    
```

Fig-2: Importing modules

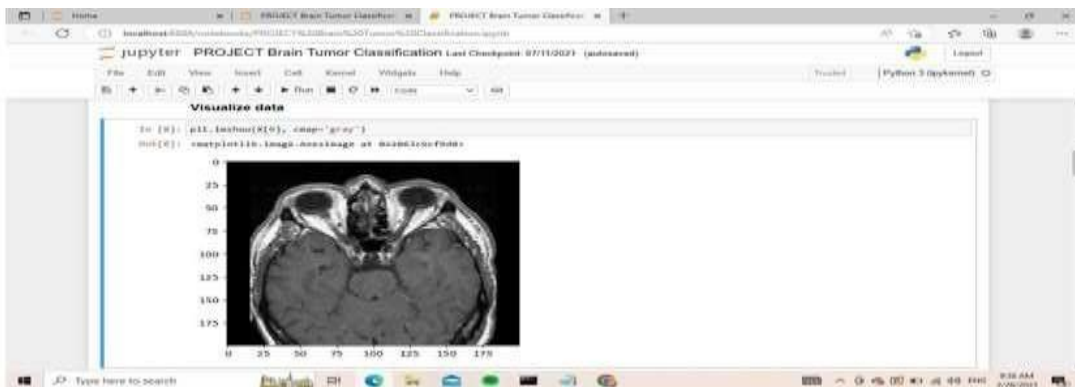
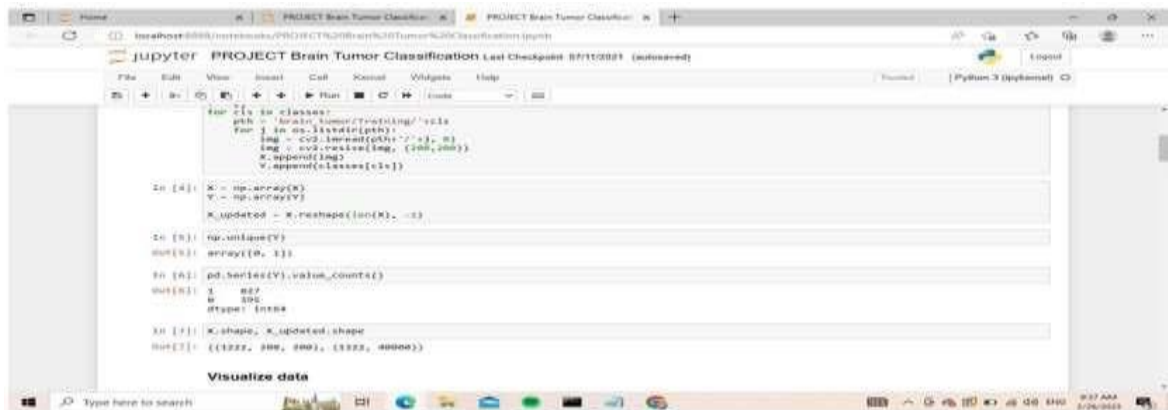


Fig-3: visualize data



```

for i in classes:
    path = 'brain_tumor/training/'+i+ '/'
    for j in os.listdir(path):
        img = cv2.imread(path+'j', 0)
        img = cv2.resize(img, (100,100))
        X.append(img)
        Y.append(Classes[i])

In [4]: X = np.array(X)
        Y = np.array(Y)
        X_updated = X.reshape((len(X), -1))

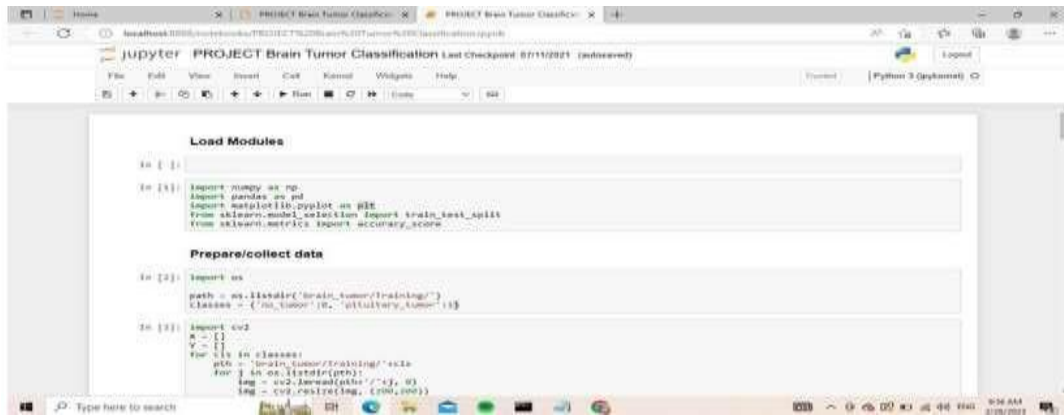
In [5]: np.unique(Y)
Out[5]: array([0, 1])

In [6]: pd.Series(Y).value_counts()
Out[6]: 1    827
        0    595
        dtype: int64

In [7]: X.shape, X_updated.shape
Out[7]: ((1227, 288, 288), (1227, 4096))

Visualize data
    
```

Fig-5: Displaying shapes of X and Y



```

Load Modules

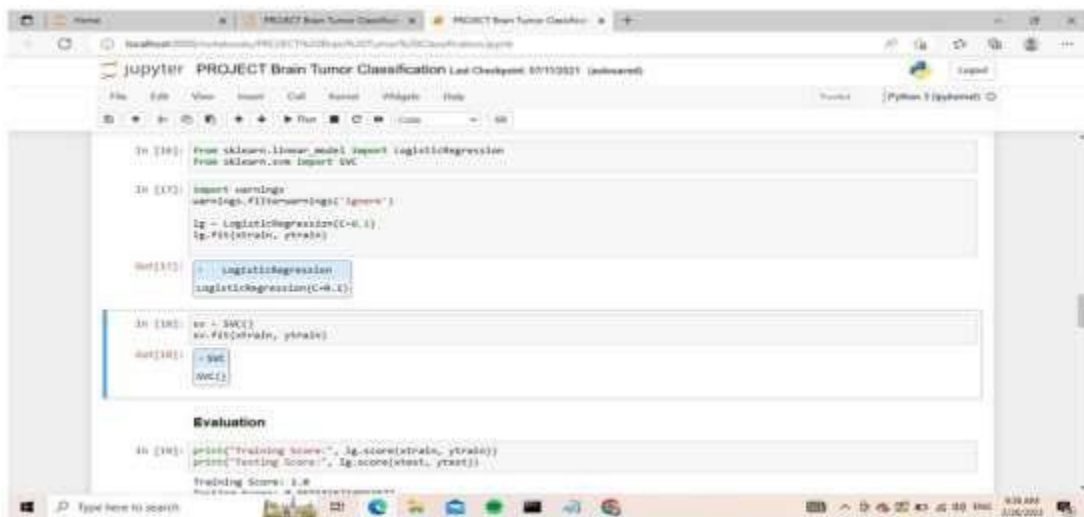
In [1]:
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

Prepare/collect data

In [2]:
import os
path = os.listdir('brain_tumor/training/')
Classes = ('no_tumor', 'glioma_tumor')

In [3]:
import cv2
X = []
Y = []
for i in classes:
    path = 'brain_tumor/training/'+i+1
    for j in os.listdir(path):
        img = cv2.imread(path+'/'+j, 0)
        img = cv2.resize(img, (60,60))
    
```

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(C=0.1)

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

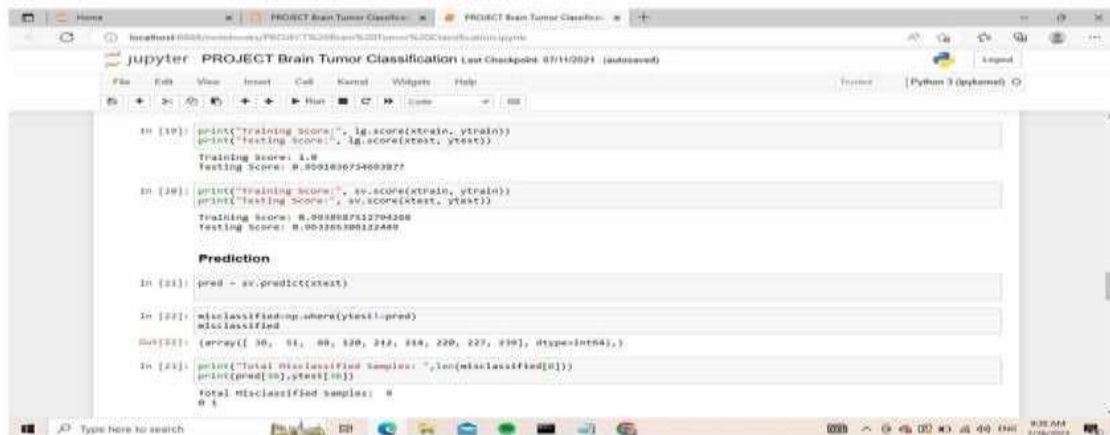
Out[18]: SVC()

Evaluation

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

Training Score: 1.0
Testing Score: 0.9991830734003877
    
```

Fig-7: Perform Logistic regression and SVM



```

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

Training Score: 1.0
Testing Score: 0.9991830734003877

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

Training Score: 0.999882712794208
Testing Score: 0.999285390122480

Prediction

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

In [22]: misclassified=np.where(ytest!=pred)
misclassified

Out[22]: (array([ 30,  61,  88, 120, 242, 248, 220, 227, 230]), dtype=int64,)

In [23]: print("Total Misclassified Samples:", len(misclassified[0]))
print(pred[misclassified[0]])

Total Misclassified Samples: 9
0 1
    
```

Fig-8: Prediction

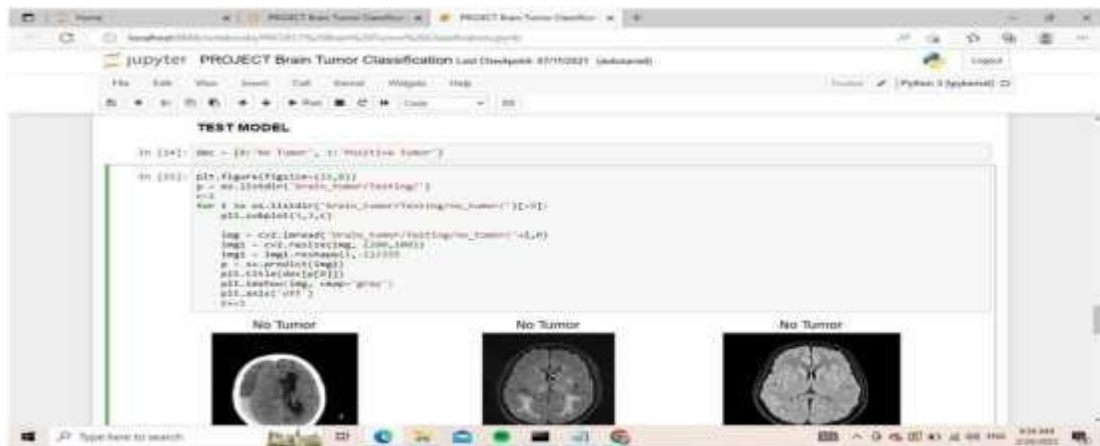


Fig-9: Testing module

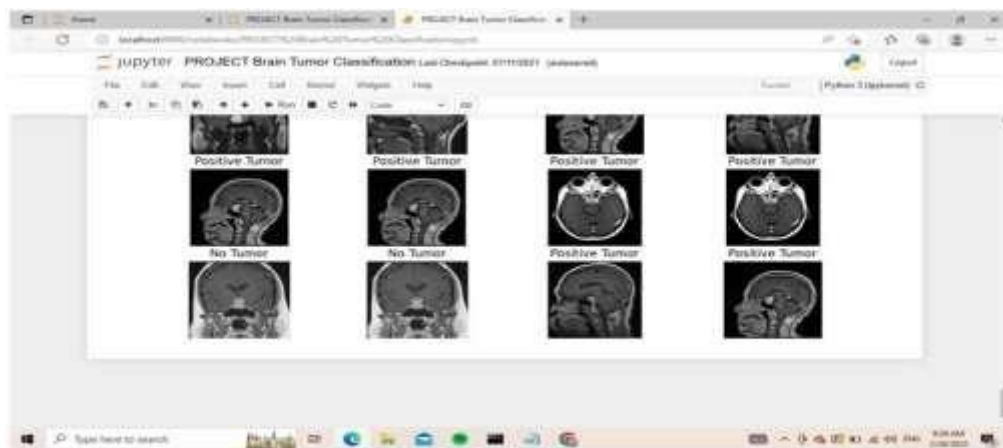


Fig-10: Displaying different types of tumors.

6 CONCLUSION AND FUTURE WORK

We proposed a computerized method for the segmentation and identification of a brain tumour using the Convolution Neural Network. The input MR photographs are read from the local device and converted to grayscale images using the file location. An adaptive bidirectional filtering method is used to pre-process these photographs in order to reduce noise from the raw photos. To locate the tumor site in the MR images, binary thresholding and convolution neural network segmentation are applied to the denoised image. With an accuracy of 84%, the proposed model yields promising results with no errors and requires a significant reduction in processing time. Research indicates that in order to achieve more accurate findings, the proposed method needs a large training dataset. However, gathering medical data is a time-consuming procedure in the field of medical image processing, and in some rare cases, the datasets may not be available. The recommended approach needs to be reliable enough to locate tumors from MR images in each of these cases. By utilizing algorithms with minimal or no training data, known as poorly trained algorithms, the proposed method can be further enhanced in detecting anomalies. Algorithms that are self-learning would also aid in increasing processing speed and accuracy.



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