BRAIN TUMOR DETECTION

A PROJECT REPORT

for

DATA MINING TECHNIQUES (CSE3054)

in

B.Tech – Computer Science and Engineering

by

YATIN PATNI (20BDS0272)

KHYATI PAREEK (20BDS0299)

PRERNA SINGH (20BDS0310)

Under the Guidance of

DR. ARUP GHOSH

Assistant Professor Sr. Grade 1, SCOPE

Vellore Institute of Technology
(Deemed to be University under section 3 of UGC Act, 1956)

School of Computer Science and Engineering

December, 2021

<u>DECLARATION BY THE CANDIDATE</u>

We hereby declare that the project report entitled **"BRAIN TUMOR DETECTION"** submitted by us to Vellore Institute of Technology University, Vellore in partial fulfillment of the requirement for the award of the course **Data Mining Techniques (CSE3054)** is a record of bonafide project work carried out by us under the guidance of **Dr. Arup Ghosh**. We further declare that the work reported in this project has not been submitted and will not be submitted, either in part or in full, for the award of any other course.

Place : Vellore

Date : December 1st, 2021

Signature

Prerna Singh

Prerna Singh

Khyati

Khyati Pareek

Yatin

Yatin Patni

Brain Tumor Detection

Abstract

Brain tumors are the most widely recognized and dangerous type of tumors. A brain tumor is a mass, of abnormal cells in the brain. The effects of brain tumors depend upon the area and size of the tumor. It is exceptionally vital to recognize the tumor as soon as possible. MRI can be utilized to distinguish the cancer by examining the MRI yet this technique is extremely tedious for a large number of cases.

Amongst brain tumors, gliomas are the most well-known and forceful, prompting an extremely short future. Hence, proper timely medical treatment is a vital step to increase chances of getting better. Magnetic resonance imaging or MRI is a generally utilized imaging method to evaluate these tumors, yet the enormous measure of information delivered by MRI forestalls manual segmentation in a sensible time, restricting the utilization of exact quantitative estimations in the clinical practice. Thus, automatic segmentation techniques are required, however, the large spatial and structural variability among brain tumors make automatic segmentation a challenging problem. In this project, we will propose methods to overcome the aforementioned difficulties.

KEYWORDS: Feed forward back propagation neural network, Support vector machine, Discrete wavelet transform, Texture features by gray level co-occurrence matrix (GLCM).

I. INTRODUCTION

Brain tumors are the most common and aggressive form of tumors. A brain tumor is a collection, or mass, of abnormal cells in your brain. Symptoms of brain tumors depend on the location and size of the tumor. It is very crucial to detect the brain cancer as early as possible. MRI can be used to detect the brain cancer by analyzing the MRI but this procedure is very time consuming for vast number of cases. Sadly, there many of these tumors are discovered late time when symptoms of the disease are present and when the tumor has become large, making it very difficult to treat or remove the tumor and dangerous. Therefore, the diagnosis of the tumors in the brain are based on image analysis of the MRI, and it is a saver method and doesn't affect the human body because it doesn't use any radiation.

II. BACKGROUND

The need for an automated and well-organized brain tumor MR Image Classification and Diagnosis system has increased with accurate results for proper treatment directions (therapy and surgery planning). In this project we have used SVM classification. In machine learning, support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis.

III. Literature Survey

1. Neural Network Based Brain Tumor Detection Using Wireless Infrared Imaging Sensor.

The machine learning based Back propagation neural network framework has major practical importance in acknowledging data and in the segmentation of the image of the tumor. The pictures are characterized into 2 classes. While analysis, the machine learning based Back propagation neural network uses 30 example images for the process of tumor classification. Then, the classification is carried out utilizing two methods, Adaboost Classifier and machine learning based Back Propagating Neural Network. Contrasting with Adaboost, NN has an extra benefit of recognizing whether the tumor is in beginning phase or in an advanced stage.

2. Brain Tumor Detection and Classification with Feed Forward Back-Prop Neural Network.

Feed-forward backprop neural network is utilized to present a classification of the tumors in the image. This strategy results high exactness and less iteration identification which further diminishes the consumption time. This technique just identifies area and size of tumor. This method comprises of a four phases preprocessing: image extraction, feature testing, Rough set Theory (Binary Classifier), and Feed forward Neural Network.

3. Review of Brain Tumor Detection using Pattern Recognition Techniques.

In this paper, a detailed work of the brain tumor detection has been performed, utilizing image processing segmentation and other methods. Initially the information is scanned thoroughly and then is preprocessed. Later image division is performed which incorporates Edge Detection based, Clustering, Region growing, Fuzzy based, Thresholding based, etc. In the later stages, feature selection and grouping is done which doesn't produce precise outcomes.

4. Image Analysis for MRI Based Brain Tumor Detection and Feature Extraction Using Biologically Inspired BWT and SVM.

Magnetic resonance images were segmented into ordinary tissues and then preprocessing was applied to avoid undesirable noise. Later a skull stripping algorithm to improve the skull stripping execution was performed, and moreover Berkeley wavelet was utilized to transform and segment the images and support the vector machine to classify the tumor stage by studying feature vectors and region of the tumor.

Through this way, they could study texture based and histogram-based features with a known classifier for the classification of the brain tumor from MR brain images. By the means of this, we had the option to demonstrate great execution. The different performance factors likewise demonstrate that the proposed algorithm gives better outcome by improving certain boundaries like mean accuracy, sensitivity, specificity, and dice coefficient.

5. Classification of Brain MRI Tumor Images: A Hybrid Approach.

The proposed hybrid approach was applied to brain MRI Images in order to properly classify brain tumor. Automatic brain tumor detection approach lessens the manual labelling time and keep away from the human mistakes. This approach is a mix of DWT (Discrete Wavelet Transform) utilized for feature extraction, and the principal component analysis (PCA) for decreasing the features. For the characterization of MR images, the Support Vector Machine has been utilized.

6. Brain Tumor Classification Using Svm and Knn Models for Smote Based MRI Images.

This paper proposed a strategy that joins the discrete wavelet revamp (DWT) with Principal Component Analysis (PCA) to characterize the brain MRIs into Normal and tumor affected one. Image thresholding has been applied for segmentation purposes. The proposed work is tried with KNN models. To adjust the samples in the dataset classes, SMOTE sampling method has been embraced. This serves to improve the proposed model's classification accuracy by 3.4% on an average.

7. An improved implementation of brain tumor detection using segmentation based on soft computing.

Image segmentation is a significant and challenging factor in the medical image segmentation. This paper depicts segmentation method consisting of two phases. In the principal phase, the MRI brain image is obtained from patients' database. In that film, artifact and noise are removed after that HSom is applied for image segmentation. The HSom is the extension of the conventional self-organizing map used to classify the image row by row. In this lowest level of weight vector, a higher value of tumor pixels, computation speed is achieved by the HSom with vector quantization.

8. Brain Tumor Detection Using Artificial Neural Networks.

In this Brain Tumor Detection Using Artificial Neural Networks. That proposed method presented an automated recognition system for MR imaging using Artificial Neural Networks (ANNs). It was observed that when the Elman network was used during the recognition process, the duration time and the accuracy level were high, compared with other ANNs systems. This neural network has sigmoid function which increases the level of accuracy of the tumor segmentation. The number of neurons in the input layer is equal to the number of extracted features from brain MRI image.

9. Automated Brain Tumor Detection and Identification Using Image Processing and Probabilistic Neural Network Techniques.

In this paper, modified image segmentation techniques were applied on MRI scan images in order to detect brain tumors. Also in this paper, a modified Probabilistic Neural Network (PNN) model that is based on learning vector quantization (LVQ) with image and data analysis and manipulation techniques is proposed to carry out an automated brain tumor classification using MRI-scans. The simulation results showed that the modified PNN gives rapid and accurate classification compared with the image processing and published conventional PNN techniques. Simulation results also showed that the proposed system out performs the corresponding These results also claim that the proposed LVQ-based PNN system decreases the processing time to approximately 79% compared with the conventional PNN which makes it very promising in the field of in-vivo brain tumor detection and identification.

10. <u>Detection and classification of brain tumor using Artificial Neural Network from EEG Images.</u>

This proposed a new method of detection and classification of brain tumor using artificial neural networks from EEG images. In this proposed method, the authors decomposed EEG signals which were obtained from the brain, were decomposed using Discrete Wavelet Transform (DWT). These decomposed coefficients of DWT of normal EEG signals and abnormal EEG signals were trained by feed forward back propagation neural networks. The size of these coefficient matrices was equal to the number of neurons in the neural network classifier. Then, the decomposition of source EEG signals were carried out and these decomposed coefficients were classified using trained patterns of neural network classifiers. The authors tested their proposed EEG signal classification algorithms over 50 EEG signals and achieved 80% of average classification accuracy.

11. <u>Analysis of MRI images using Data Mining for detection of Brain Tumor</u>

In this project, we have developed a system for the detection of Brain Tumor using K-means clustering algorithm using the interface of GUI in MATLAB. The GUI developed is very powerful and better than the traditional method as it is faster and accurate. As faster the Input given, faster is the output we get because the system is accurate and redundant free. So, we are able to detect the tumor early.

12. Brain Tumor Segmentation based on extremely randomized Forest with high-level features

Another cerebrum tumor division technique was proposed. This comprised of an Extra-Trees classifier dependent on nearby and setting highlights characterized on Tlc, T2 and Flair X-ray successions. The nearby highlights were characterized as the force, mean power and angles on the voxel under investigation, while the setting highlights were characterized as the mean forces and inclinations in close via planes. These features are proved to be very competitive and enhanced the regions of brain tumor ,allowing an overall seventh position among thirty-one methods on the test set of BraTS2013 challenge data-set.

13. An Intelligent System for Early Assessment and Classification of Brain Tumor

There are many different Data Mining techniques to detect Brain tumor but Pre - Processing and Skull Removal Process will definitely increase the performance. Here, the system will give the advice based on the results to the patient and some description about the medicines and tests in a simple way that helps them to identify and understand the result more accurately. We can also increase the accuracy by using classifier like GA-SVM and helps in increasing decision-making capacity.

14. Brain Tumor Detection and Classification using SVM

Different techniques use different classifiers, here we are use an advanced classifier i.e., Support Vector Machine (SVM). In this proposed work, image was pre-processed with median filtering and skull stripping method. It showed better performance than the non-linear SVM classification approach. In this approach, we extract all the features using Grey Level Co-occurrence Matrix (GLCM) and the SVM classifier is used for more accuracy or more accurate results. The authors achieved sensitivity of 91.52%, Specificity of 67.74% and Accuracy of 83.33%.

15. Brain Tumor Detection and Classification Using Histogram Equalization and Fuzzy Support Vector Machine Approach

It proposed brain tumor detection and classification using Histogram Equalization (HE) technique and Fuzzy Support Vector Machine (FSVM) classification approach. The brain MRI image, using histogram equalization was pre-processed and segmented the suspicious portion from the image based on Markov Random Field (MRF) algorithm for segmentation method. MRF method increased the tumor segmentation accuracy through which the performance of the proposed method was improved.

Therefore, features were extracted based on texture, fractal and histogram features, finally the classification was done by using a support vector machine approach. The reason behind this improvement of classification was that this proposed method enhanced the brain image for obtaining better tumor segmentation results.

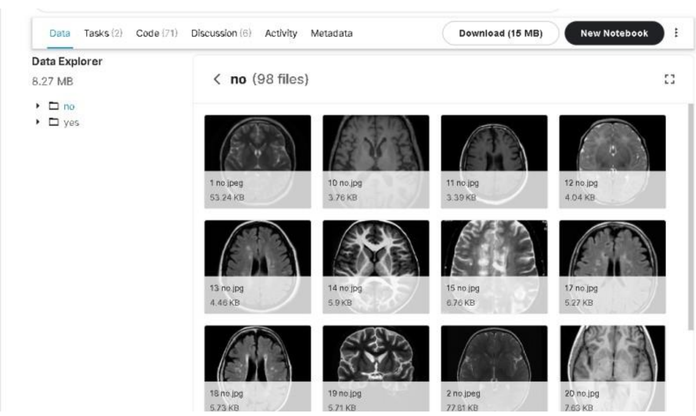
IV. DATASET DESCRIPTION & SAMPLE DATA

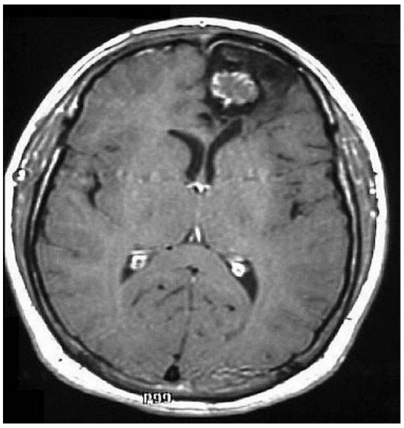
We have a dataset that contains 2 folders: ‘yes’ and ‘no’ which contains a total of 253 Brain MRI Images. The folder ‘yes’ contains 155 Brain MRI Images that are tumorous and the folder ‘no’ contains 98 Brain MRI Images that are non-tumorous. We have downloaded the dataset from Kaggle which is a platform that provides the users a various data sets on many topics.

The link for our data set is given below and can be easily accessed.

<u>SAMPLE DATA</u>

https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection





As the data set contains nearly 255 images so we can’t consider this as a big dataset. Therefore, there are not enough examples to train the neural networks and to tackle the data imbalance we use the concept of data augmentation.

As we don’t have large data, we therefore have altered it by rotating the images at different angles and by flipping it which will be considered as new images, so by this we enlarge our data to some extent.

After the data augmentation, now the data set consists of:

1085 positive and 980 examples, resulting in 2065 example images in total.

Note: These 2065 images also contain the 253 original images. They are in the folder named “Augmented Data”.

V. PROPOSED ALGORITHM WITH FLOWCHART

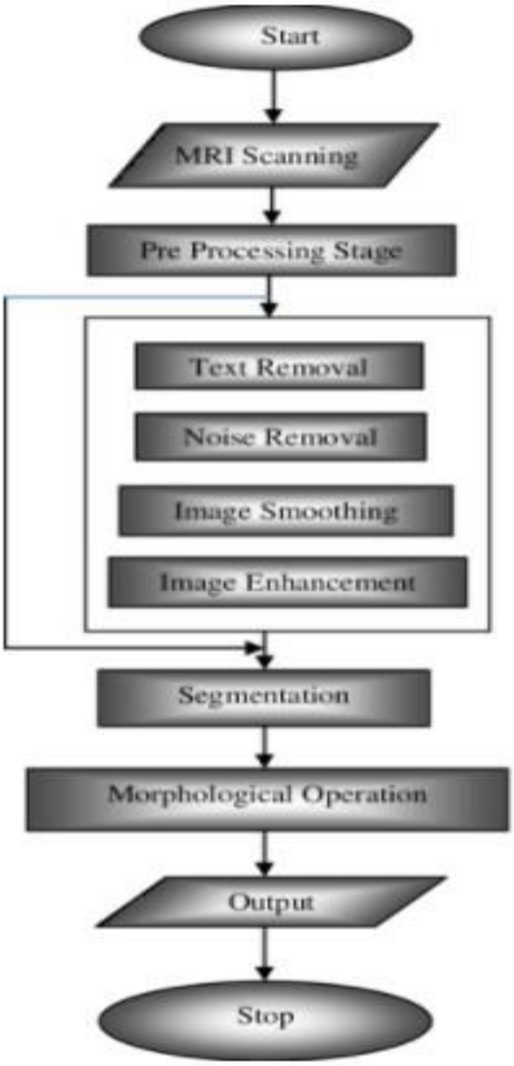


Fig: Flowchart of brain tumor detection and segmentation.

Modules and stages explanation:

Pre-processing stage

The main task of pre-processing is to enhance the precision of the MR images and also to get it suitable for further processing by a human or machine vision system. The grayscale image is quite important for many purposes, such as segmentation of images, extraction of features and classification of images using the (rgb2gray) function of the MATLAB software used to convert the RGB image to the Grayscale images. The MATLAB (adjust) function has been used to increase the Contrast in some image by assigning the values of the input intensity of the image to new values such that the information is saturated at low and high input data level.

Sometimes MRI images contain noise that must be discarded and removed. The causes of this noise are due to the high frequency of radio waves and the patient's movement during the MRI. Anisotropic filtering used anisotropic diffusion filter is an image filtering method. The algorithm is implemented on the MATLAB software used function *(anisodiff.m).*

Image segmentation stage

The segmentation technique a significant role in the processing of images. Segmentation results will be used to obtain quantitative information from images, including clustering, thresholding, etc.

Threshold segmentation

Threshold segmentation technology plays an essential part in the processing of images. The threshold segmentation is used to extract the various regions from the whole image according to the difference in intensity.

Morphological operation

Typically, applied on the binary images (black & white images) where the pixels value is between 0 and 1. This work is used in post-processing to enhance the threshold segmentation by removing noise and to filter out smaller areas. The first step is very important to remove undesired pixels as noise by filling the holes that can be described as a distortion in the image. Where the small holes fill the white pixel in the dark background by dark pixel and the holes dark in the white region will convert to a white pixel. Filling region algorithm based on set dilations, complements, and intersections. In the second step, erosion operations are intended to eliminate pixels from the boundary area of the objects.

Tumor Outline

Tumor outline is an additional step used to determine the shape of the tumor and external limits. Image pixel subtraction operators take two images as an input of the same size and produce as output a third image; whose pixels values are the values obtained by subtraction between the two images.

Feature extraction stage

Extracting features is to extract and transform details for input information into several features, called a feature vector, by decreasing the pattern of data representation. The components set will obtain the extracted from the input data (image) to execute the classification task.

Tumor classification stage

The system consists of two panels: the feature extraction stage (based on preprocessing and post-processing techniques) and the classification stage (based on artificial intelligence algorithms and SVM).

Support vector machine

SVM is a supervised machine learning algorithm used to classify data for different classes based on a separating hyperplane. Although there two main types of SVM classifications: linear and non-linear. The input vectors are assigned to the feature vector using the kernel function that directly calculates the dot product in the feature space. The hyper-plane is formed in a dimensional space separated into two classes, which Optimizes the distance between each other and closes the training sets. This hyper- plane is used as a basis for classifying vectors of unknown objects (testing objects).

PSEUDOCODE:

1. Upload your dataset or some images in MATLAB for tumor detection.
2. Input images one by one to check if tumor is present or not. To do this do the following:
3. First, filter your images by giving certain values in the pre-defined function an iso diff_function ().
4. The image data is filtered and all kinds of noise is removed from the image.
5. After filtration, we applied various techniques to check like thresholding, morphological operation etc.
6. On basis of calculation by applying discrete fusion and diffusion, we did various calculation and check tumor by operations.
7. To display, we applied outlines where tumor is detected and by removing the skull part and checking for more details in an image.
8. Therefore, by applying data mining techniques and operation we have calculated if tumor exists or not.

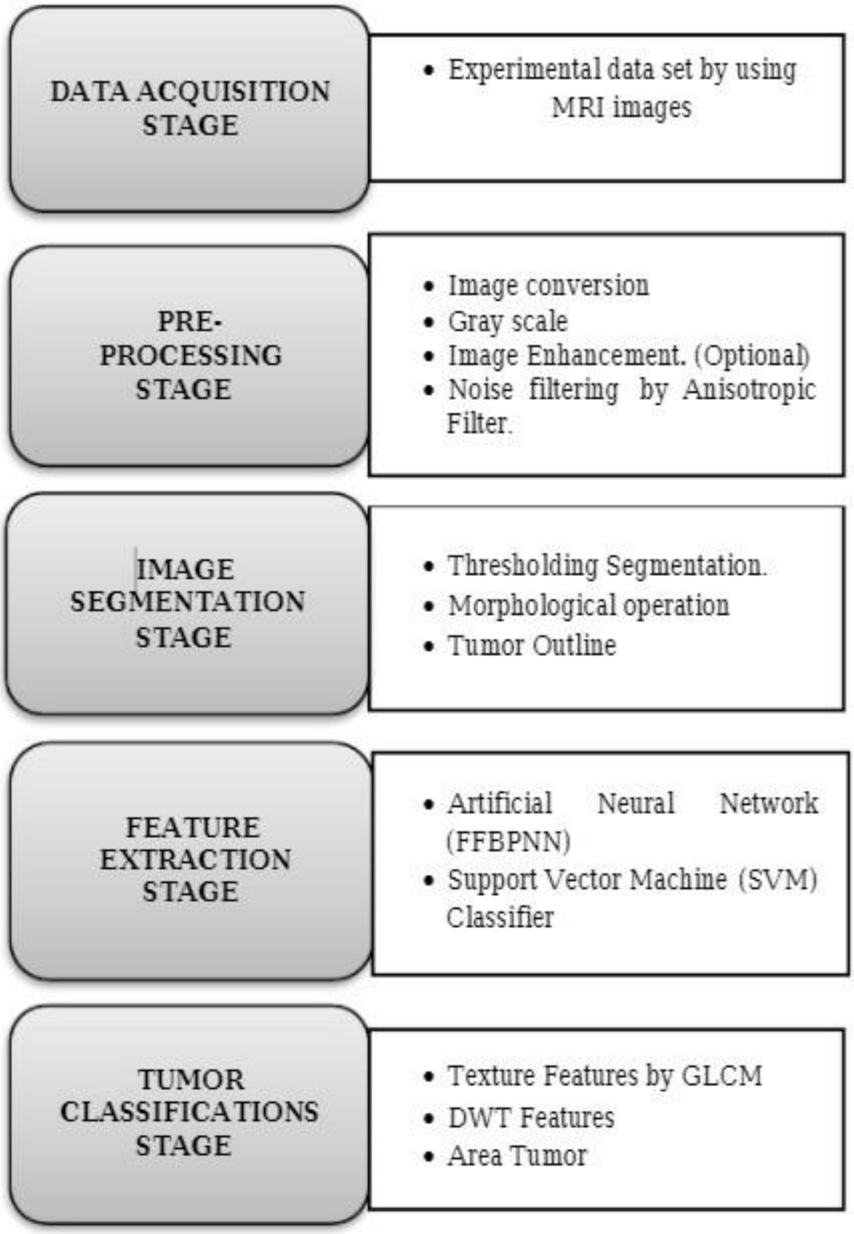


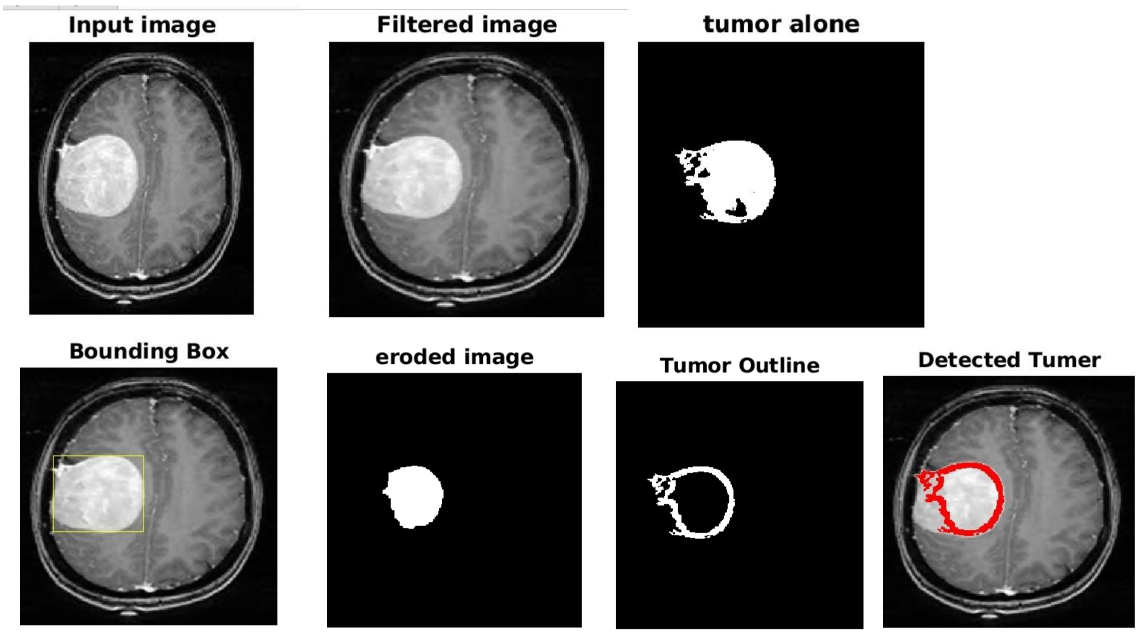
Fig: Different stages of the proposed methodology.

VI. EXPERIMENTS RESULTS

The experimental results provided by the work technique depicted for the segmented outcome and the extracted tumor region are given in below images. Concerning the variables with high normalized importance such as kurtosis, contrast, entropy, energy, correlation, and all other variables are not reflecting

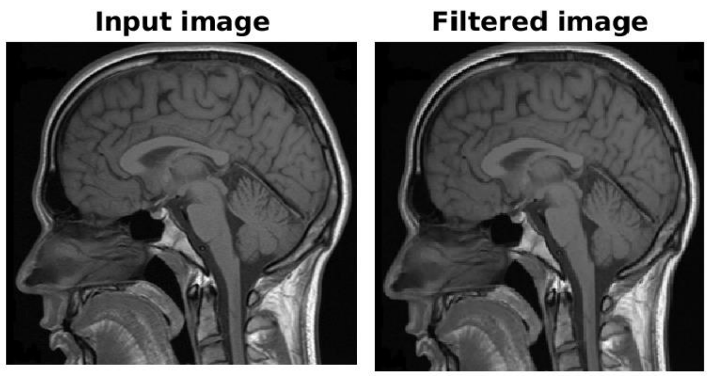
a threshold of classification to categories of brain tumor categories on their own. This is because other factors need to be involved and added to the set of independent variables.

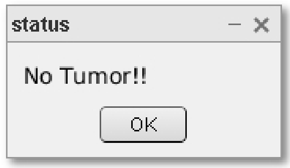
Experiment 1:



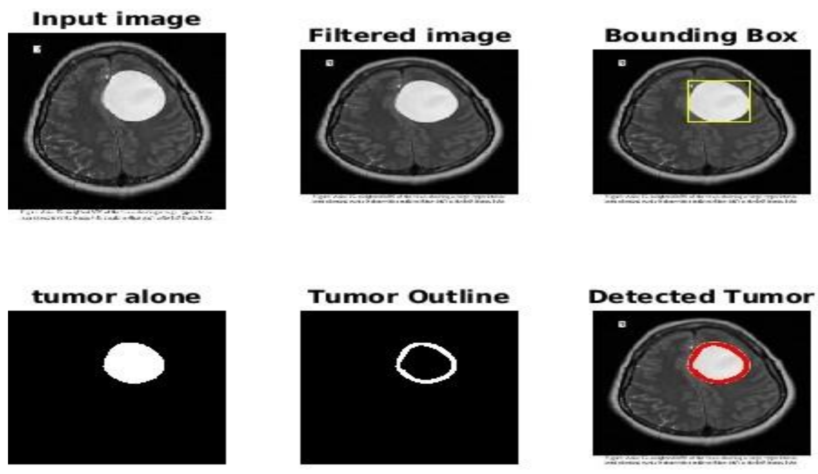
Result of pre-processing AND segmentation (a) Original MRI input image, (b) Anisotropic diffusion filtering, (c) Proposed thresholding segmentation, (d)Eroded and Morphological operation, and (e) Tumor outline. (f) Detection

Experiment 2:





Experiment 3:



VII. COMPARATIVE STUDY / RESULTS AND DISCUSSION

The training dataset images for which the extracted features have been practiced using the classification process classifier (SVM), while the test dataset is not trained using the SVM classifier, mostly the statistical and textural features have been extracted. The precision of the training and testing images were analyzed by comparison focused on the classification of (normal, benign, and malignant) tumors cells for FFBPN, while SVM was centered on the classification of (benign and malignant) tumors cells. The accuracy or classification performance rate is the effectiveness of the relevant classification for the overall amount of classification checks. The output of the algorithm proposed can be computed using predictive values. There are four predictive values: true positive values (TP), true negative values (TN), false-positive values (FN), and false-positive (FP). This was used to measure the efficiency of the work results presented to the MRI images by sensitivity, specificity, and accuracy as shown in equation used. The calculation for test images (images used for test after the training process) is shown.

VIII. CONCLUSION AND FUTURE WORK

This work aimed to submit an Automated algorithm for detecting brain tumors from MRI images by Artificial Neural Networks and SVM. The data collected the images and prepared by pre-processing and post-processing processes to make it suitable for detection. Analysis of statistical features has been used to extract features from images; attributes calculated from Gray comatrix features dependent on the (GLCM) of images. We use MRI images, preprocesses them, and then trains on the set of images with our model, and achieve accuracy of 98% with loss of 0.08%. This model can be further trained 22 for even better results, by increasing the size of the dataset and/or the number of epochs. Image segmentation plays a significant role in medical image processing as medical images have different diversities. For brain tumor segmentation, we used MRI scan images. MRI is most vastly used for brain tumor segmentation and classification. In our work, we used SVM algorithm to classify Brain Tumors. It is clear from our results that accuracy of our model is only increasing over time and loss is decreasing over time. This is a good thing, as it shows our model was effective, and results were accurate. Finally; the proposed algorithm, the FFBPN, gives the best results by detecting and classifying brain tumors according to the extraction feature achieved results with a precision of 97% while the SVM has low accuracy.

The proposed system effectively classifies the images of the brain tumor of the MRI. This work can be extended in the future according to expansion the data base to include the other type of MRI images, developing the algorithm to detect and diagnoses brain tumor to the 3D images MRI. Using the algorithm to extend to the analysis of other medical images, such as CT and PET images.

IX. REFERENCES

- https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=8599180

- https://www.ijcseonline.org/pdf_paper_view.php?paper_id=1189&21-IJCSE-15-2017.pdf
- http://downloads.hindawi.com/journals/ijbi/2017/9749108.pdf
- https://www.sciencedirect.com/science/article/pii/S1877050917326455
- https://www.ijareeie.com/upload/2016/march/43_Brain.pdf
- https://academicjournals.org/journal/JCREO/article-full-text-pdf/B7F32593408.pdf
- https://www.researchgate.net/publication/281161679_Image_Processing_Techniques_for_Atomatic_Detection_of_Tumor_in_Human_Brain_Using_SVM
- https://www.researchgate.net/publication/4321983_Brain_Tumor_Detection_Using_Color-Based_K-Means_Clustering_Segmentation
- https://ieeexplore.ieee.org/abstract/document/8071613/
- https://www.sciencedirect.com/science/article/pii/S1877050917326455
- https://academic.oup.com/neuro-oncology/article/19/1/139/2452339
- http://csjournals.com/IJCSC/PDF8-2/3.%20Sunila.pdf
- https://link.springer.com/content/pdf/10.1007/s41095-019-0139-y.pdf
- https://ieeexplore.ieee.org/abstract/document/7319032
- Senthilkumar N C and Pradeep Reddy Ch, *(Classification) Grouping the Users Based on their Web Search Using Fuzzy Logic*, International Journal of Pure and Applied Mathematics, Vol. 116, No. 21, 2017
- https://arxiv.org/pdf/1706.06411.pdf#:~:text=Feed%2Dforward%20back%2D%20prop%20 neural,further%20reduces%20the%20consumption%20time.&text=MRI%2C%20Brain%20t umor%2C%20Statistical%2C,Thresholding%20Feed%2DForward%20backward%20 network

Appendix

Complete Code:

```
clc
close all

%% Input
[I,path]=uigetfile('*.jpg','select a input image'); % its a modal that opens the dialogue box and lists out all the files in the drive
str=strcat(path,I);
s=imread(str); %Reading image data

figure; %creates a new window with default values
imshow(s); %display image in that window
title('Input image','FontSize',20);

%% Filter
num_iter = 10;
delta_t = 1/7; %stability value max 0.25
kappa = 15; %conduction coefficient
option = 2; %to check again..........
disp('Preprocessing image please wait…………');
inp = anisodiff_function(s,num_iter,delta_t,kappa,option);
inp = uint8(inp); % converts value in range as unsigned integer array
inp=imresize(inp,[256,256]);
if size(inp,3)>1
inp=rgb2gray(inp);
end
figure;
imshow(inp);
title('Filtered image','FontSize',20);

%% thresholding
sout=imresize(inp,[256,256]);
t0=mean(s(:)); %intensity of an image
th=t0+((max(inp(:))+min(inp(:)))./2);
for i=1:1:size(inp,1)
for j=1:1:size(inp,2)
if inp(i,j)>th
sout(i,j)=1;
else
sout(i,j)=0;
end
end
end

%% Morphological Operation

label=bwlabel(sout);
stats=regionprops(logical(sout),'Solidity','Area','BoundingBox'); % calculates the parameters by measuring distance bw each pair of pixels
density=[stats.Solidity];
area=[stats.Area];
high_dense_area=density>0.7;
max_area=max(area(high_dense_area));
tumor_label=find(area==max_area);
```

```
tumor=ismember(label,tumor_label); %returns an array containing logical 1 (true)
where the data in A is found in B. Elsewhere, the array contains logical 0 (false)

if max_area>200
figure;
imshow(tumor)
title('tumor alone','FontSize',20);
else
h = msgbox('No Tumor!!','status');
%disp('no tumor');
return;
end
%% Bounding box

box = stats(tumor_label);
wantedBox = box.BoundingBox;
figure
imshow(inp);
title('Bounding Box','FontSize',20);
hold on;
rectangle('Position',wantedBox,'EdgeColor','y');
hold off;


%% Getting Tumor Outline - image filling, eroding, subtracting
% erosion the walls by a few pixels

dilationAmount = 5; %inbuilt fn that reduces the image thickness
rad = floor(dilationAmount);
[r,c] = size(tumor);
filledImage = imfill(tumor, 'holes');

for i=1:r
for j=1:c
x1=i-rad;
x2=i+rad;
y1=j-rad;
y2=j+rad;
if x1<1
x1=1;
end
if x2>r
x2=r;
end
if y1<1
y1=1;
end
if y2>c
y2=c;
end
erodedImage(i,j) = min(min(filledImage(x1:x2,y1:y2)));
end
end
figure
imshow(erodedImage);
title('eroded image','FontSize',20);

%% subtracting eroded image from original BW image
```

```
tumorOutline=tumor;
tumorOutline(erodedImage)=0;

figure;
imshow(tumorOutline);
title('Tumor Outline','FontSize',20);

%% Inserting the outline in filtered image in red color

rgb = inp(:,:,[1 1 1]);
red = rgb(:,:,1);
red(tumorOutline)=255;
green = rgb(:,:,2);
green(tumorOutline)=0;
blue = rgb(:,:,3);
blue(tumorOutline)=0;

tumorOutlineInserted(:,:,1) = red;
tumorOutlineInserted(:,:,2) = green;
tumorOutlineInserted(:,:,3) = blue;


figure
imshow(tumorOutlineInserted);
title('Detected Tumer','FontSize',20);

%% Display Together

figure
subplot(231);imshow(s);title('Input image','FontSize',10);
subplot(232);imshow(inp);title('Filtered image','FontSize',10);

subplot(233);imshow(inp);title('Bounding Box','FontSize',10);
hold on;rectangle('Position',wantedBox,'EdgeColor','y');hold off;

subplot(234);imshow(tumor);title('tumor alone','FontSize',10);
subplot(235);imshow(tumorOutline);title('Tumor Outline','FontSize',10);
subplot(236);imshow(tumorOutlineInserted);title('Detected Tumor','FontSize',10);



function diff_im = anisodiff_function(im, num_iter, delta_t, kappa, option)
fprintf('Removing noise\n');


fprintf('Filtering Completed !!');

% Convert input image to double.
im = double(im);

% PDE (partial differential equation) initial condition.
diff_im = im;

% Center pixel distances.
dx = 1;
dy = 1;
dd = sqrt(2);

% 2D convolution masks - finite differences.
```

```matlab
hN = [0 1 0; 0 -1 0; 0 0 0];
hE = [0 0 0; 0 -1 1; 0 0 0];
hW = [0 0 0; 1 -1 0; 0 0 0];
hNE = [0 0 1; 0 -1 0; 0 0 0];
hSE = [0 0 0; 0 -1 0; 0 0 1];
hS = [0 0 0; 0 -1 0; 0 1 0];
hSW = [0 0 0; 0 -1 0; 1 0 0];
hNW = [1 0 0; 0 -1 0; 0 0 0];


% Anisotropic diffusion.
for t = 1:num_iter

% Finite differences. [imfilter(.,.,'conv') can be replaced by conv2(.,.,'same')]
nablaN = imfilter(diff_im,hN,'conv');
nablaS = imfilter(diff_im,hS,'conv');
nablaW = imfilter(diff_im,hW,'conv');
nablaE = imfilter(diff_im,hE,'conv');
nablaNE = imfilter(diff_im,hNE,'conv');
nablaSE = imfilter(diff_im,hSE,'conv');
nablaSW = imfilter(diff_im,hSW,'conv');
nablaNW = imfilter(diff_im,hNW,'conv');
end

% Diffusion function.
if option == 1
cN = exp(-(nablaN/kappa).^2);
cS = exp(-(nablaS/kappa).^2);
cW = exp(-(nablaW/kappa).^2);
cE = exp(-(nablaE/kappa).^2);
cNE = exp(-(nablaNE/kappa).^2);
cSE = exp(-(nablaSE/kappa).^2);
cSW = exp(-(nablaSW/kappa).^2);
cNW = exp(-(nablaNW/kappa).^2);
elseif option == 2
cN = 1./(1 + (nablaN/kappa).^2);
cS = 1./(1 + (nablaS/kappa).^2);
cW = 1./(1 + (nablaW/kappa).^2);
cE = 1./(1 + (nablaE/kappa).^2);
cNE = 1./(1 + (nablaNE/kappa).^2);
cSE = 1./(1 + (nablaSE/kappa).^2);
cSW = 1./(1 + (nablaSW/kappa).^2);
cNW = 1./(1 + (nablaNW/kappa).^2);
end

% Discrete PDE solution.
diff_im = diff_im + ...
delta_t*(...
(1/(dy^2))*cN.*nablaN + (1/(dy^2))*cS.*nablaS + ...
(1/(dx^2))*cW.*nablaW + (1/(dx^2))*cE.*nablaE + ...
(1/(dd^2))*cNE.*nablaNE + (1/(dd^2))*cSE.*nablaSE + ...
(1/(dd^2))*cSW.*nablaSW + (1/(dd^2))*cNW.*nablaNW );
end
```