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Detection and Segmentation of Tumor and Edema of a Brain Using Artificial Neural Network

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Abstract : *Brain Tumor Segmentation In Magnetic Resonance Imaging (Mri) Is Considered A Complex Procedure Because Of The Variability Of Tumor Shapes And The Complexity Of Determining The Tumor Location, Size, And Texture. In This Paper, A Method For Fully Automated Segmentation And Classification Of Brain Tumor With No User Intervention Has Been Developed. Here We Propose Morphological Level Sets Segmentation To Isolate Tumor, White Matter, Grey Matter And Edema Regions. Initially Input Image Is Pre-Processed Using Edge Preserved Anisotropic Diffusion Filter Which Evolves Using Orientation Driven Edge Preserved Smoothening Operations. This Intensity Normalized Image Set Is Capable Of Level Set Functions, I.E., The Interface Of A Level Set Function Can Either Expand Or Shrink Toward The Object Boundary. Finally Shape And Texture Feature Attributes Are Extracted For Neural Network Classification.*
Keywords *- Anisotropic Diffusion Filter , Brain Tumor , Edge Preserved Smoothing Operations, Magnetic Resonance Image (Mri), , Morphological Level Sets Segmentation.*

I. Introduction

Brain Tumor Is One Of The Most Common Brain Disease. Brain Is The Most Complicated Part Of Our Body. The Brain Tumor Is Unwanted Growth Of Cells Inside Human Brain Growing In Uncontrollable Manner. Tumor Cells Of The Brain And Show A Rapid Growth By Extending Into The Healthy Brain Tissues. Brain Tumors Have Different Characteristics Such As Size, Shape, Location, And Image Intensities. They May Deform Neighboring Structures And If There Is Edema With The Tumor, Intensity Properties Of The Nearby Region Change. There Are Two Types Of Tumor Malignant And Benign. Malignant Tumor Contains Cancerous Cells And Grows Rapidly. Benign Are Easily Distinguishable And Have A Slow Growth Rate. Benign Tumor Are Least Aggressive Their Growth Are Self-Limited And They Don't Spread Into Other Tissues. Malignant Tumor Contain Cancerous Cells And They Cannot Be Removed Easily Which May Lead To Death Hence Malignant Tumors Are More Harmful Than Benign. In Adults, The Most Common And Cancer-Causing Tumor Type Is Glial Tumors That Have A High Mortality Rate. Over 90% Of All Tumors In Persons Over 20 Years Are Glial Tumors [1].

There Are Various Techniques Used For Detection Of Human Brain Tumor. Image Segmentation Is The Separation Of An Image Into Segments Called Classes Or Subsets, According To One Or More Characteristics Or Features, And Enhancing Areas Of Interest By Separating Them From The Background And Other Areas [2]. In The Mri Is The Widely Used Imaging Technique In Neuroscience And Neurosurgery For These Applications. Manual Segmentation Of Brain Mri Images Is A Time Consuming And Tiring Process That Can Show Differences When Performed By Different Experts[3]. Brain Tissue Segmentation Especially Tumor And Edema Is Quite A Difficult Task Because Of Nonhomogeneous Intensity Distribution, Unclear Boundaries, Complex Shape And Background Noise. However, Segmentation Of The Tissues Of The Brain, Especially Tumor And Edema Is A Quite Difficult Task Because Of The Nonhomogeneous Intensity Distribution, Background Noise, Complex Shape, Unclear Boundaries, And Low Intensity Contrast Between Adjacent Brain Tissues [4]. The Fact That Not All Glial Tumors Have A Clear Boundary Between Necrotic And Active Parts, And That Some May Not Have Any Necrotic Parts Also Complicates Segmentation [5].As Mri Uses Magnetic Waves, So It Is Unsuitable For Patients With Pacemakers And Metal Implants.Brain Tissues Are Segmented Into Three Components As White Matter, Grey Matter And Cerebrospinal Fluid (Csf)[6-10]. Glcm Texture Features Allows Us To Segment Both Healthy (Gm, Wm And Csf) And Pathological (Tumor And Edema) Tissues Of The Brain. For Extracting Tumor From Mri Image Denoised Image Was Used In K-Means. Although This Is Useful For Diagnosing Many Neurological Diseases, Segmenting Pathological Regions Of Brain Is Crucial In Patients With Tumor And Edema. Studies That Segment Only Tumor [11]–[16] And Tumor And Edema Together [5], [17] Use Patient Data With Different Type Of Tumors.

Various Studies [5], [12], [13], [15] Performed Segmentation On Patients With Glial Tumor. The Algorithm Has Two Stages, First Is Preprocessing Of Mri Image And Second Is Segmentation And Performing Analytical Operations. Various Image Segmentation Techniques Are Applied On Mri For Detection Of Tumor.

Low Signal-To-Noise Ratio Or Contrast-To-Noise Ratio Decreases The Correct Segmentation Ratio Regardless Of The Method Used [18]. As A Solution To This Problem, Filtering Methods That Are Space-Invariant Like Low-Pass Filtering Is Applied To The Images.

Major Drawbacks Of The Conventional Filtering Methods Are Blurring Of The Object Boundaries And Important Features And Suppression Of Fine Structural Details In The Image, Particularly Small Lesions [19]. This Limitation Is Resolved By The Space-Variant Filters By Using Local And Feature-Dependent Techniques. Examples

Of These Filters Are Local Shape-Adaptive Template Filtering, Linear Least-Squares Error Filtering, And Anisotropic Diffusion Filtering. Gerig Et Al. [18] Compared The Nonlinear Anisotropic Diffusion

Filter That Is Proposed By Perona And Malik [20] With A Wide Range Of Filters Used To Eliminate The Random Noise Of The Mr Image. They Demonstrated That Anisotropic Diffusion Filter Blurs Homogeneous Regions, Increase The Ratio Of Signal-To-Noise And Sharpens The Object Borders. This Filter Also Diminishes Noise And

Reduces Partial Volume Effects, Thus Greatly Reducing Subsequent Operator-Dependent Errors In Misclassified Training Points [19]. For Brain Tumor Classification There Are Four Steps: The Firstly Roi Segmentation Was Done Where The Boundary Of The Tumor In An Mr Image Was Identified, Feature Extraction From Roi Was Second Step The Third Step Was The Feature Selection, The Last Step Was The Classification Process In Which Learning A Classification Model Using The Features.

II. Proposed System

The Existing System Was Able To Determine Tumor But It Was Unable To Give Shape And Size Of Tumor As Well As It Was Unable To Classify Tumor And Detect It At Its Earliest Stage Which Was Overcame In Proposed System.

Proposed System Detects The Type Of Tumor By Using The Value Of Scaling Factor:

Scaling = 0 To 30 Benign Tumor

Scaling = 30 To 40 Benign Tumor

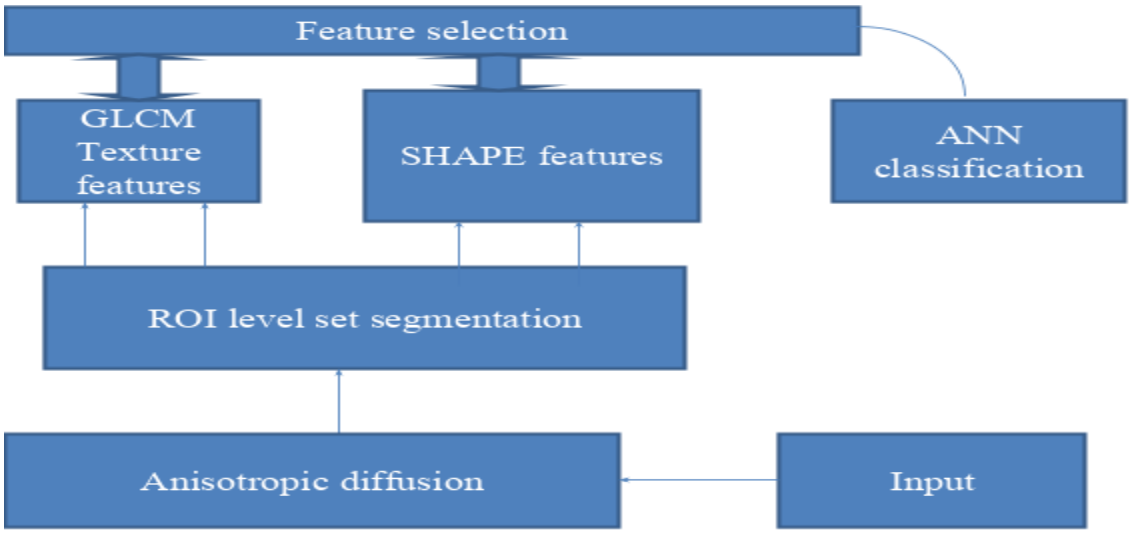
Scaling = 40 To 50 Malignant Tumor

Quality Of Imaging, Difficulty Of Brain Structures, And The Necessity Of Accurate Segmentation Make It Difficult To Qualifying The Performance Of The Segmentation Algorithms Of Brain[21]. We Used Dice Similarity Index, Which Is A Region-Based Coefficient That Measures Spatial Overlap Of Ground Truth (Manual Segmentation) And Segmentation Result[22], Sensitivity, And Specificity To Evaluate The Results. Let Tp Be True Positive, Fn Be False Negative, Fp Be False Positive, And Tn Be True Negative. Dice Coefficient Is Calculated As

$(2 * Tp)/((2 * Tp) + Fp + Fn)$

The Sensitivity Is $Tp/(Tp + Fn)$

And The Specificity Is $Tn/(Fn + Tn)$.



2.1 Anisotropic Diffusion

Anisotropic Diffusion Is A Technique Aiming At Reducing Image Noise Without Removing Significant Parts Of The Image Content, Typically Edges, Lines Or Other Details That Are Important For The Interpretation Of The Image. Anisotropic Diffusion Resembles The Process That Creates A Scale Space, Where An Image Generates A Parameterized Family Of Successively More And More Blurred Images Based On A Diffusion Process. Each Of The Resulting Images In This Family Are Given As A Convolution Between The Image And A 2d Isotropic Gaussian Filter, Where The Width Of The Filter Increases With The Parameter. This Diffusion Process Is A Linear And Space-Invariant Transformation Of The Original Image. Anisotropic Diffusion Is A Generalization Of This Diffusion Process: It Produces A Family Of Parameterized Images, But Each Resulting Image Is A Combination Between The Original Image And A Filter That Depends On The Local Content Of The Original Image. As A Consequence, Anisotropic Diffusion Is A Non-Linear And Space-Variant Transformation Of The Original Image. Anisotropic Diffusion Filters Usually Apply Spatial Regularization Strategies. It Applies The Law Of Diffusion On Pixel Intensities To Smooth Textures In An Image. A Threshold Function Is Used To Prevent Diffusion To Happen Across Edges, And Therefore It Preserves Edges In The Image. This Makes It Very Interesting If You Want To Remove Noise, But Do Not Want To Smooth Out The Edges Of Your Image, For Instance If You Want To Use These Edges To Segment The Image, Without Being Perturbed By The Noise.

2.2 Roi Level Segmentation

In Order To Measure A Morphometric Parameter Within An Image (Area Or Counting For Example), The Computer Program Needs To Distinguish Wanted From Unwanted Areas. This 'Region Of Interest' Or Roi Usually Is Determined On The Basis Of Pixel Intensity Values Or User-Determined Areas (By Drawing And Subsequent Masking). The Process Of Separating Objects Of Interest From Uninteresting Objects Is Called Segmentation. When Images Are Segmented On The Basis Of Intensity The User Defines A Range Of Pixel Intensity Values That Encompasses Interesting Objects. When The User Defines A Gray-Scale Intensity Value, Above Which The Object(S) Lie And Below Which Encompasses The Background, The Image Is Said To Be Thresholded, And The Process Is Referred To As Thresholding. If The Objects Of Interest Have A Median Range Of Intensity Values, Defining A Slice Of Possible Intensity Values Between 0 (Black) And 255 (White) Can Segment The Image And Separate The Objects From Background. The Range Of Roi Intensity Values Is Often Referred To As A Density Slice A Segmented Image Based On Thresholded Intensity Is Literally Separated Into Uninteresting From Interesting Pixels. Once Segmented, The Pixels Of The Image Can Be Reassigned The Intensity Values Of Either 0 (Uninteresting) Or 1 (Interesting). In This Operation Geometry Within The Remains The Same, However The Grayscale Image Is Transformed Into A Binary Image Consisting Of Only Intensity 1 Or 0. Determining Morphometric Is A Process Of Counting Adjacent Pixels With A Value Of 1 And Ignoring Those With A Value Of 0.

2.3 Glcm Texture Features

The Gray Level Co-Occurrence Matrix (Glcm) And Associated Texture Feature Calculations Are Image Analysis Techniques. Given An Image Composed Of Pixels Each With An Intensity (A Specific Gray Level), The Glcm Is A Tabulation Of How Often Different Combinations Of Gray Levels Co-Occur In An Image Or Image Section. Texture Feature Calculations Use The Contents Of The Glcm To Give A Measure Of The Variation In Intensity (A.K.A. Image Texture) At The Pixel Of Interest. A Statistical Method Of Examining Texture That Considers The Spatial Relationship Of Pixels Is The Gray-Level Co-Occurrence Matrix (Glcm), Also Known As The Gray-Level Spatial Dependence Matrix. The Glcm Functions Characterize The Texture Of An Image By Calculating How Often Pairs Of Pixel With Specific Values And In A Specified Spatial Relationship Occur In An Image, Creating A Glcm, And Then Extracting Statistical Measures From This Matrix. (The Texture Filter Functions, Described In Texture Analysis Cannot Provide Information About Shape, That Is, The Spatial Relationships Of Pixels In An Image.

2.4 Shape Features

The Use Of Object Shape Is One Of The Most Challenging Problems In Creating Efficient Cbir. The Object's Shape Plays A Critical Role In Searching For Similar Image Objects (E.G. Texts Or Trademarks In Binary Images Or Specific Boundaries Of Target Objects In Aerial Or Space Images, Etc.). In Image Retrieval, One Expects That The Shape Description Is Invariant To Scaling, Rotation, And Translation Of The Object And Is Naturally Either 2d Or 3d Depending On The Object. Shape Features Are Less Developed Than Their Color And Texture Counterparts Because Of The Inherent Complexity Of Representing Shapes. In Particular, Image Regions Occupied By An Object Have To Be Found In Order To Describe Its Shape, And A Number Of Known Segmentation Techniques Combine The Detection Of Low-Level Color And Texture Features With Region-Growing Or Split-And-Merge Processes. But Generally It Is Hardly Possible To Precisely Segment An Image

Into Meaningful Regions Using Low-Level Features Due To The Variety Of Possible Projections Of A 3d Object Into 2d Shapes, The Complexity Of Each Individual Object Shape, The Presence Of Shadows, Occlusions, Non-Uniform Illumination, Varying Surface Reflectivity, And So On .After Segmenting Objects, Their Shapes Have To Be Described, Indexed, And Compared. However No Mathematical Description Is Able To Fully Capture All Aspects Of Visually Perceived Shapes As Well As Shape Comparison Is Also A Very Difficult Problem. The Elusive Nature Of Shape Hinders Any Formal Analysis Of A Trade-Off Between The Complexity Of Shape Description And Its Ability To Describe And Compare Shapes Of Interest.

2.5 Feature Selection

In Machine Learning And Statistics, Feature Selection, Also Known As Variable Selection, Attribute Selection Or Variable Subset Selection, Is The Process Of Selecting A Subset Of Relevant Features (Variables, Predictors) For Use In Model Construction. Feature Selection Techniques Are Used For Four Reasons: Simplification Of Models To Make Them Easier To Interpret By Researchers/Users Shorter Training Times, To Avoid The Curse Of Dimensionality, Enhanced Generalization By Reducing Over Fitting (Formally, Reduction Of Variance) The Central Premise When Using A Feature Selection Technique Is That The Data Contains Many Features That Are Either Redundant Or Irrelevant, And Can Thus Be Removed Without Incurring Much Loss Of Information. Redundant Or Irrelevant Features Are Two Distinct Notions, Since One Relevant Feature May Be Redundant In The Presence Of Another Relevant Feature With Which It Is Strongly Correlated. Feature Selection Techniques Should Be Distinguished From Feature Extraction. Feature Extraction Creates New Features From Functions Of The Original Features, Whereas Feature Selection Returns A Subset Of The Features. Feature Selection Techniques Are Often Used In Domains Where There Are Many Features And Comparatively Few Samples (Or Data Points).

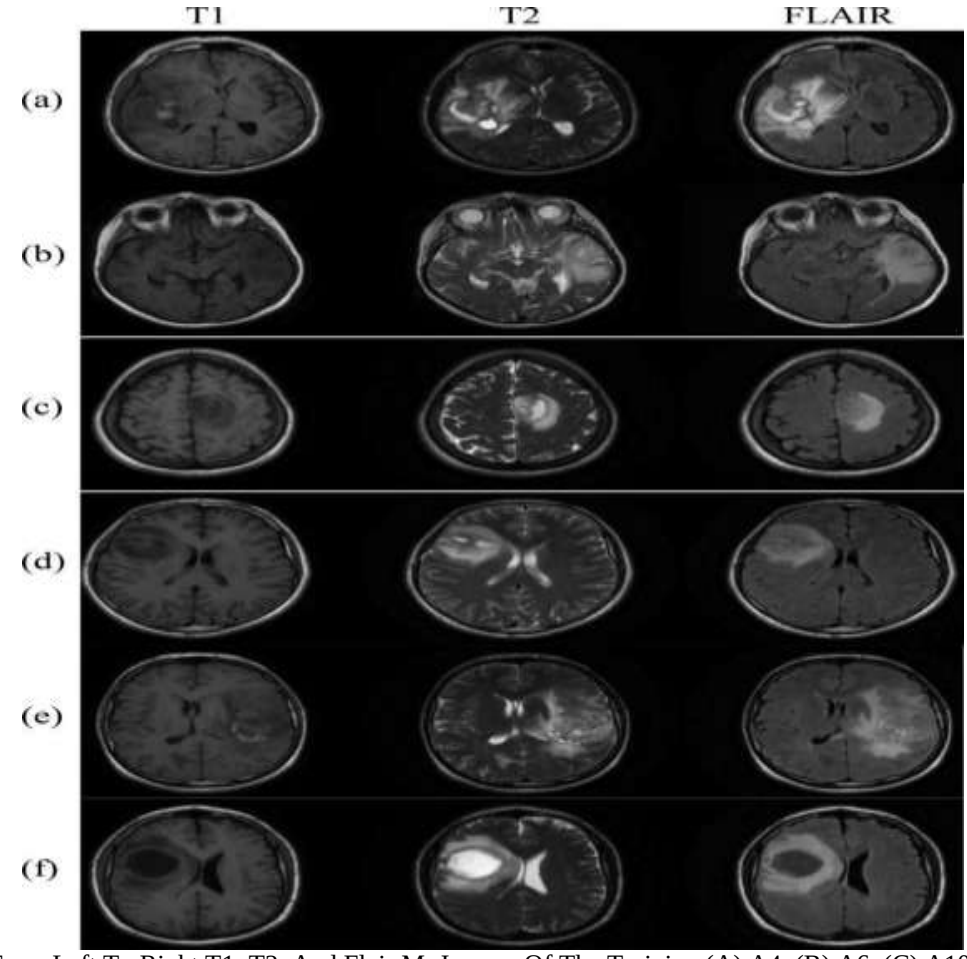


Fig. 1. From Left To Right T1, T2, And Flair Mr Images Of The Training (A) A4, (B) A6, (C) A10 And Test Patients, (D) B3, (E) B6, And (F) B7.

2.6 Ann Classification

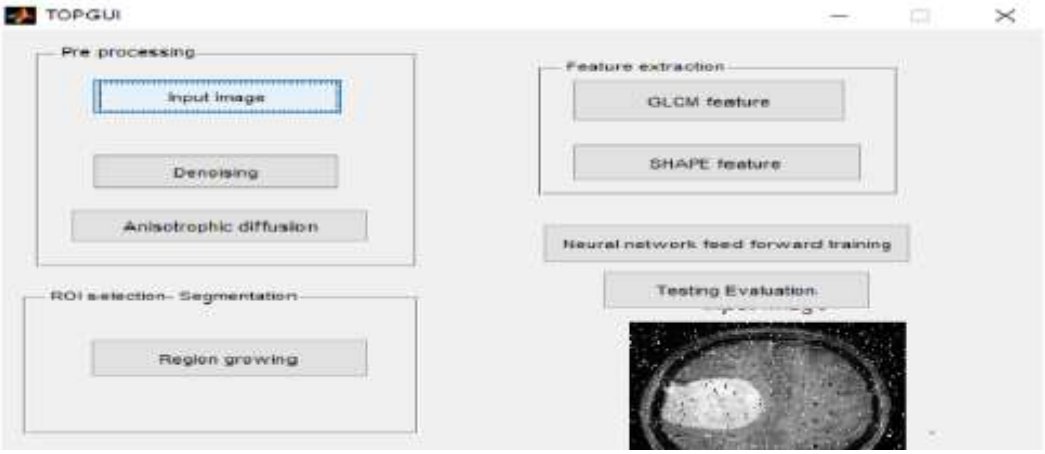
Ann Classification Is The Process Of Learning To Separate Samples Into Different Classes By Finding Common Features Between Samples Of Known Classes. For Example, A Set Of Samples May Be Taken From

Biopsies Of Two Different Tumor Types, And Their Gene Expression Levels Measured. We Can Use This Data To Learn To Distinguish The Two Tumor Types So That Later, Gene Linker Can Diagnose The Tumor Types Of New Biopsies. Because Making Predictions On Unknown Samples Is Often Used As A Means Of Testing The Ann Classifier, We Use The Terms Training Samples And Test Samples To Distinguish Between The Samples Of Which Gene Linker Knows The Classes (Training), And Samples Of Which Gene Linker Will Predict The Classes (Test). Ann Classification Is An Example Of Supervised Learning. Known Class Labels Help Indicate Whether The System Is Performing Correctly Or Not. This Information Can Be Used To Indicate A Desired Response, Validate The Accuracy Of The System, Or Be Used To Help The System Learn To Behave Correctly. The Known Class Labels Can Be Thought Of As Supervising The Learning Process; The Term Is Not Meant To Imply That You Have Some Sort Of Interventionist Role. A Step In Ann Classification Involves Identifying Genes Which Are Intimately Connected To The Known Classes. This Is Called Feature Selection Or Feature Extraction. Feature Selection And Ann Classification Together Have A Use Even When Prediction Of Unknown Samples Is Not Necessary: They Can Be Used To Identify Key Genes Which Are Involved In Whatever Processes Distinguish The Classes.

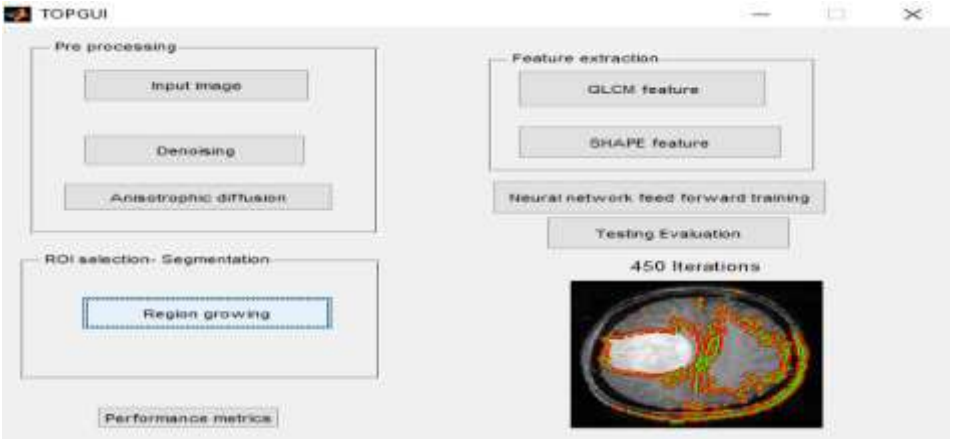
2.7 Preprocessing

We Normalized The Intensity Range Of The Images To [0 1] Range By Dividing All Intensity Values To The Maximum Intensity Value. To Improve The Signal-To-Noise Ratio, We Applied Anisotropic Diffusion Filter To The Images As A Preprocessing Step. This Powerful Filter Is Defined As A Diffusion Process. Inner Parts Of The Regions Are Smoothed And Edges Are Preserved By Estimating Local Image Structure And Using Edge Strengths And The Noise Degradation Statistics.

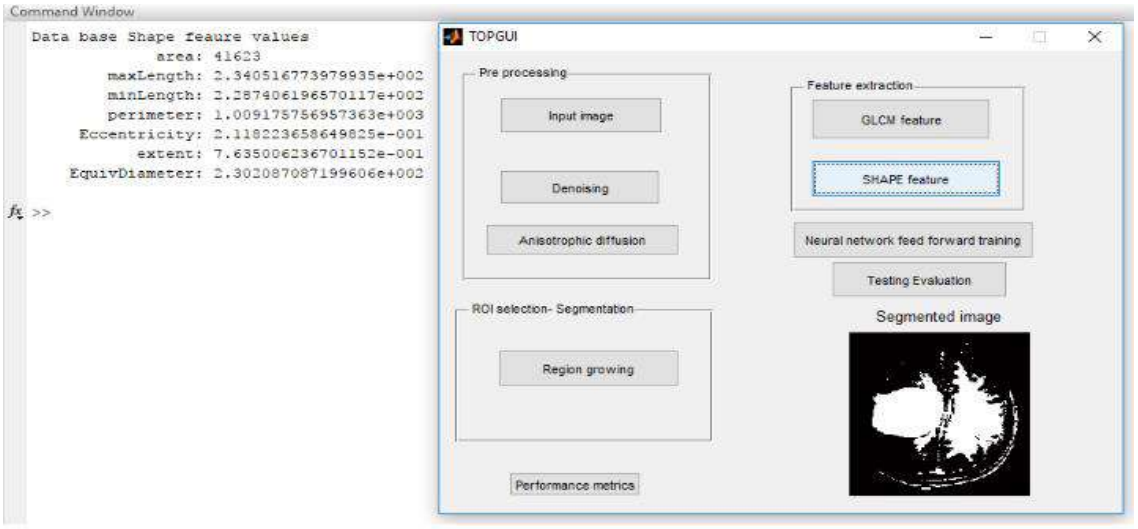
Input Image



Roi Selection



Shape Features



III. Conclusion

We Segmented Brain Mr Images Into Healthy Tissues Such As Gm, Wm, And Csf Along With The Diseased Tissues, Tumor, And Edema. To Classify The Detected Tumor Region Into Malignant And Benign And To Sharpen The Edges. Twenty Patients Suffering From The Glial Tumor Are Used. We Registered T1, T2, And Flair Mr Images Into One Coordinate System After Filtering With Anisotropic Diffusion Filter. We Developed An Algorithm That Combines Threshold And Morphological Operations For Stripping The Skull That Is Not Our Region Of Interest In This Study. We Performed Spatial Filtering Methods On These Sub Bands To Obtain Feature Vector That Will Be Used As Input To The Som. Segmentation Operation Is Performed By An Unsupervised Som Network. We Developed An Algorithm, Based On The Hit Histograms Of The Bmus Of The Output Neurons For Clustering The Som Instead Of Using An Additional Nn. We Used Dice Similarity Index, Sensitivity And Specificity To Evaluate The Performance Of The Developed Algorithm. We Compared The Results Obtained From The System To The Regions Manually Selected By The Radiology Physician. The Statistical Analysis Of The Experimental Results Has Indicated That The Developed Algorithm Can Segment Brain Mr Images With Good Accuracy. Our Overall Procedure Can Segment Wm, Gm, Csf, Tumor, And Edema From Mr Images And Requires 20s For Each Mr Volume. Our Method Showed A Moderate And Comparable Performance On This Dataset.

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