Multi Stage Classification and Segmentation of Brain Tumor Images Based on Statistical Feature Extraction Technique

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Abstract: Automatic classification of brain images has a censorious act in calm down the burden of manual characterize and developing power of brain tumor diagnosis. In this paper, Stanchion Vector Machine (SVM) method has been employed to perform classification of brain tumor images into their variety and grades. Chiefly the target is on four brain tumor categories-Normal, Glioma, Meningioma, Metastasis and the four grades of Astrocytomas, which is a conventional section of Glioma. We consult segmentation of glioma tumors, which have a large deviation in size, pattern and appearance inheritance. In this paper images are enlarged and normalized to same range in a pre-functioning stride.The enlarged images are then segmented positioned on their intensities applying 3D super-voxels. This effort analyze the SVM classifier applying variance statistical feature set the final analysis shows that for brain tumor categories and grades classification. The analyses are repeated for variance SVM categories, kernel categories and gamma points of kernel section. Analysis on the misclassification is implemented for each feature set applying specificity and sensitivity measures. At the end of this effort, we inferred that the Statistical feature Extraction(SFE) method is classifying the brain tumor categories satisfactorily but comparatively lacks in tumor grade classification. Classifying the brain tumorcan collection their material in the cloud, the cloud create it attainable to admissionourmaterialin distinction to anywhere at any time.

Keywords: *Brain tumors, SVM, normalization, Magnetic Resonance Imaging, 3D super-voxels,brain tumor classification*

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I. INTRODUCTION:

Therapeutic science is one in the middle ofabundantranges which has strideintocomputerizationmethod by establish a scheme or instrument for diagnosis. The opportunity of ancomputerizedtherapeuticfiguredeterminationinstrument, that is excessexact than personal readers can conceivablysupremacy to excesstrustworthy and reproducible brain tumorsymptomaticoperations. With that as the impieceial this job has been introduced. Brain tumors are irregular and uncheckedconceptions of units and it is accepted to be most lethal affliction. This year, asupposed 22,850 developed (12,900 men and 9,950 women) in the United States apiece will be diseased with primary timorous tumors of the brain and spinal cord [11]. Give approval to the enumeration of Brain.org 2015, 15,320 developed (8,940 men and 6,380 women) are afflicted by diseased brain tumor and their survival extent of time is very less [12] Glioma is considered as a group of brain and spinal tumors that can happen in glial units. Very large grade and low gradeare two ordinarycharacterizations of gliomatumors. Count on theaggressiveness of these tumors, they reside of dissimilarpieces, distinguishing as effectivetumor, necrosis (dead central piece), andedema (swelling). Utilizing magnetic resonance imaging(MRI), a very large spatial determinationaspect of brain can beexhibited. Standard segmentation of exacttumors is timeconsuming, not repeatable, and prone to error due to thealternative of mass, environment, shape and attendance of thesetumors. Therefore done segmentation of gliomatumorsis becoming a desired instrument for the diagnosis operation.

In distinction to the World Health Organization (WHO) report, 130 characterizations of brain tumors are label till this extent of time. Our research jobfor cause on the quadruplebiggercharacterizations of brain tumor and in distinction to which one section is glioma, which happens in glial units and it, is the most aggressive tumorsection constituting 45% of the brain tumor [7]. Astrocytoma actuality one most ordinarysection of glioma brain tumor, constitutes 34% of brain tumor and is broadly categorized under quadruple grades (Pilocytic Astrocytoma, Low-grade Astrocytoma, Anaplastic Astrocytoma and Glioblastoma (GBM)) [8]. This tumorinfluences both developed and children. The developed and exactdiscovery of the section and grade of the brain tumor can very largely influence the life of the patient by giving the right analysis. Therapeuticfiguredetermination has likely a direction and way for automating the brain tumorafflictiondiscovery and planning for analysis. In this determination, figure acquisition section and its material plays a vital role.

In the middle ofdiffering imaging modalities distinguishing as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Single Photon Emission Computed Tomography (SPECT), Magnetic Resonance Spectroscopy (MRS) and Positron Emission Tomography (PET), MRI is the most suitable method for brain figures as it is very sensitive and noninvasive. MRI is acquired with raiseddifference discrimination and in abundant planes, can benefit to characterize the exactenvironment of a lesion relative to key neuroanatomical structures [14]. This is intenselysubstantial for optimum surgical and radiotherapy planning.

With the benefit of magnetic resonance figures, Computer Aided Diagnosis (CAD) schemes are developed for brain tumordiscovery and its determination. In this determination, discriminative attendance is the substantial aspects in classification job. The dissimilarcharacterizations of attendance that can be excessed in distinction to MRI of brain are first regulation statistical attendance, second regulation statistical attendance, shape attendance and texture attendance [16]. This job centers on evaluating the best discriminating feature set in the middle of statistical attendance. Initially the statistical (first regulation and second regulation) attendance are excessed in distinction to the clinical axial MRI obtained in distinction to patients. The excessed attendance is likely as recommendation to the classifier to produce the train model file, which in turn secondhand to predict the class of unseen evidence. In literature, dissimilarcharacterization of classification methods is available.

As a two-class classification method, SVM is remarkable, since it gives better performance with respect to sparse and noisy evidence for abundant applications. SVM is a supervised learning method secondhand for evidencedetermination and design recognition, which decrease computational complexity and has a faster learning proportion. The evidencedetermination performed utilizing SVM can be classification or regression. With kernel capacity's, binary SVM classifier can be extended for solving multiclass classification problems. This job employed SVM as the classifier, for classifying the brain tumorcharacterization as Normal, Glioma, Meningioma, Metastasis and brain tumor grades of Astrocytoma (section of Glioma) as Pilocytic Astrocytoma, Lowgrade Astrocytoma, Anaplastic Astrocytoma and Glioblastoma (GBM). This method was repeated for dissimilar SVM characterization (C-SVC, nu SVC, one-class SVM, epsilon-SVR, nu-SVR), Kernel characterization (linear, polynomial, radial basis capacity, and sigmoid, pre-computed kernel), costs, and values of n-fold cross validation and gamma values for kernel capacity. In distinction to the determination, the most preferable kernel capacity's for section and grade classification is also inferred.

Classifying the brain tumorcan accumulation their material in the cloud, the cloud create it attainable to admissionourmaterialin distinction to anywhere at any time.Benefit-Oriented Architecture benefits to use applications as a benefit for other applications regardless the section of vendor, product or technology. Therefore, it is possible to exchange of evidence between applications of dissimilar vendors without additional programming or making changes to benefits

II. RELATED WORK

The MR personal brain figures are classified into its distinguishinggrouputilizing supervised techniques like artificial neuralnet jobs, support vector machine, and unsupervised techniques like self-organization map (SOM), fuzzy c means,utilizing the feature set as a discrimination capacity. Othersupervised classification techniques, distinguishing as k-nearestneighbors (k-NN) also group pixels based on theirsimilarities in each feature [3]. Classification of MR figureseither as normal or irregular can be done via both supervisedand unsupervised techniques [2].Komal et al., [2] suggest a computerizationscheme thatperforms binary classification to detect the attendance of braintumor. The evidence set constitutes 212 brain MR figures. It takesMR brain figures as recommendation, performs pre-mothering, excessctstexture attendancein distinction to segments and classification is performedutilizing machine learning algorithms distinguishing as Multi-LayerPerceptron (MLP) and Naive Bayes. It has been concludedwith an accuracy of 98.6% and 91.6% respectively.

NamithaAgarwal et al., [4] suggest a method where first and second regulation statistical attendance is secondhand for classification of figures. In this paper, investigations have been performed to compare texture based attendance and wavelet-based attendance with ordinarily secondhand classifiers for the classification of Alzheimer'saffliction based on T2-weighted MRI brain figure. It has been concluded that the first and second regulation statistical attendance are significantly better than wavelet based attendance in terms of all performance measures distinguishing as sensitivity, accuracy, training and testing time of classifiers. [17] Suggest the brain tumor discovery and its section classification schemeutilizing MR figures. In distinction to the figures, the tumor region is segmented and then texture attendance of that region is excessed utilizing Gray Level Co-appendence Matrix(GLCM) like energy, difference, correlation and homogeneity [4].

For classification, neuro-fuzzy classifier is adopted. GladisPushpa et al., [19] suggest a methodology that combines the intensity, texture and shape based attendance and classifies the tumor region as white matter, Gray matter, CSF, irregular and normal area utilizing SVM. Principle Component Determination (PCA) and Linear Discriminant Determination (LDA) are secondhand to reduce the number of attendance in classification. [13] Performed a binary classification to investigate the use of design classification methods for distinguishing primary gliomasin distinction to metastases, and very large grade tumor (section3 and section4) in distinction to low grade (section2). This scheme has a sequence of steps including ROI definition, feature excessction, feature selection and classification. The excessed attendance includes tumor shape and intensity characteristics as well as rotation invariant texture attendance. Feature subset selection is performed utilizing Support Vector Machines (SVMs) with recursive feature elimination. Our job is compared with this job, since both jobs are related to tumorcharacterization and grades.

In our research job, the classification method has been secondhand to classify brain tumorcharacterization and grades of distinguishingtumorsectionutilizingdissimilar levels of statistical feature excessctionmethods. For classification, the supervised machine learningalgorithm–Support Vector Machine (SVM) has beenemployed. In distinction to the determination, the suitable feature set thatdiscriminates a tumorcharacterization and grades with improvedperformance has been label. Accuracy, distinguishingity andsensitivity measures have been secondhand to analyze the result ofeach section and grade

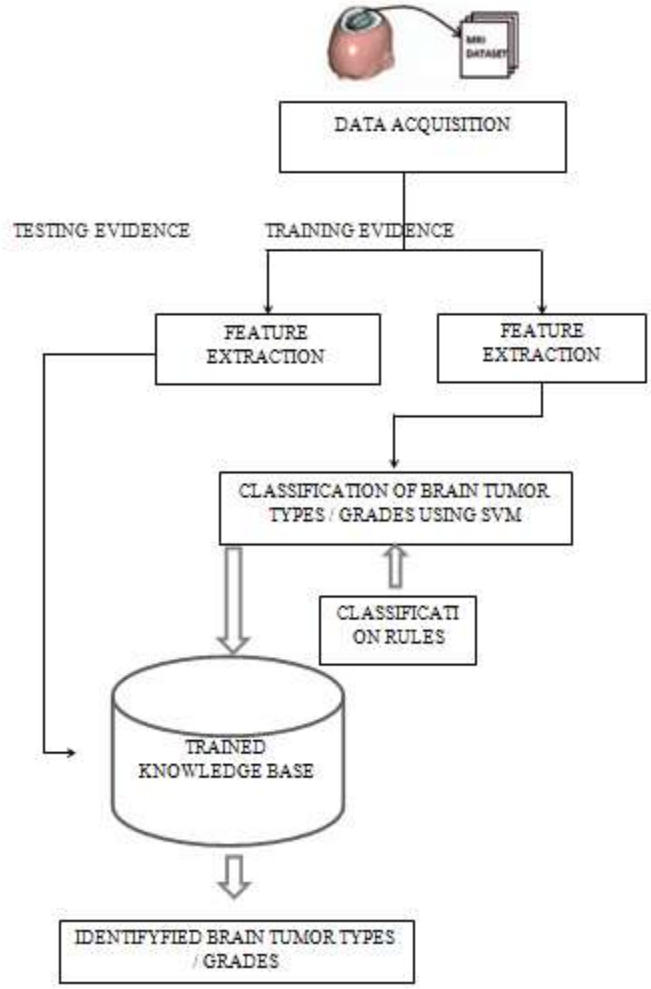
III. PROJECT DESIGN

The suggest scheme initially takes the axial MRI of brain obtained in distinction to patients for classification and evaluation. Thebrain tumor section figures as well as brain tumor grade figuresof distinguishing section are divided into training and test evidence set. Theattendance distinguishing as first regulation and second regulation statistical attendanceare excesses in distinction to the training set. Then the feature set islikely as recommendation to the SVM classifier to produce the model file.In distinction to the testing figures evidence set, attendance are excesses andlikely to the produced model file to identify the section and gradeof brain tumor at both levels.

A.Data Set

The evidence set of axial Magnetic Resonance Imaging (MRI), are collected in distinction to the subjects of differing brain tumor characterization and grades to perform classification utilizing SVM.

The brain tumor characterization considered in our scheme is Normal, Glioma, Meningioma and Metastasis as shown in Figure.



2. The environment and size of dissimilar section of brain tumors are clearly visible in the following Figure

Figure 1,An overall system design

Figure.2, Brain tumor types

The brain tumor grades of Astrocytoma which is the most ordinary section of Glioma brain tumor are Grade I – PilocyticAstrocytoma, Grade II - Low-grade Astrocytoma, Grade III -Anaplastic Astrocytoma and Grade IV - Glioblastoma (GBM)[5].

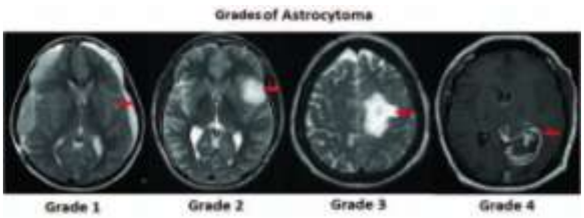


Figure 3,Grades of Astrocytoma.

The figures collected in distinction to dissimilar patients are grouped into two sets for utilizing it during training and testing stages ofthe scheme.

Table 1,Evidence set Enumeration for Brain Tumor Section

Brain tumorcharacterization	**No of Figures**		
	Training Figures	***Testing Figures***	***Total Figures***
Section 1	34	14	48
Section2	45	19	64
Section3	28	10	38
Section4	41	17	58

The evidence set (Table II) for brain tumor section identification resides of about 208 figures out of which 70% of figures are considered for training and 30% of figures are secondhand as test set. The 208 brain tumor section figures have the composition as shown in the table below

Table 2, Evidence set enumeration for brain tumorgrades of astrocytoma

Brain tumorgrades	**No of Figures**		
	Training Figures	***Testing Figures***	***Total***
Grade 1	38	16	54
Grade 2	37	20	57

Grade 3	15	6	21
Grade 4	54	27	81

IV FEATURE ENHANCEMENT

Finally in this stage, the segmentation job is encoded by classification via neural net job. Artificial neural net jobs (ANNs) are powerful computational models inspired by biological personal neural scheme. They have been widely secondhand in real-time applications distinguishing as differing therapeutic diagnosis issues, thanks to their parallel architecture. In this case we label our results into two classes, i.e. tumor core and everything else.

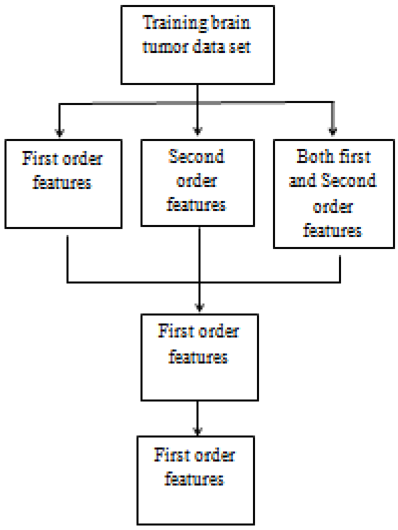


Figure4, Extracted features likely as input to the classifier.

The statistical figure attendance namely first regulation attendance (mean, variance, skewness, kurtosis and entropy) and secondregulation attendance (difference, correlation, homogeneity and energy)are excesscted in distinction to the figures. The first regulation attendance iscalculated utilizing the histogram of the recommendation figure. The secondregulation attendance is excessed in distinction to the GLCM (Gray Level CohappenenceMatrix) of recommendation figures.

Attendance excessed and classification of brain tumor characterization and grades utilizing this attendance are pictorially depicted in the Figure

V.SUPPORT VECTOR MACHINE

Support vector machine is a supervised method secondhand to find design and perform classification and regression determination.

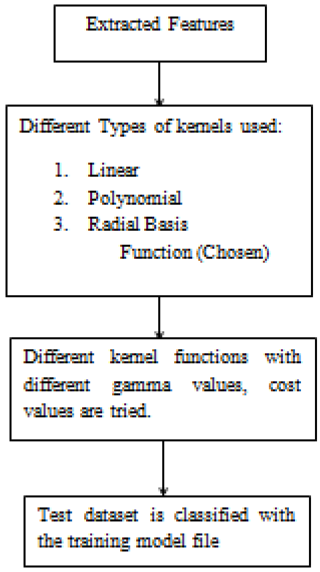


Fig. 5, SVM classifier.

Likely a set of training evidence marked with class, the SVM classifier builds a model that assigns new unseen evidence into a group. This can be secondhand for multiclass classification utilizing kernel tricks. Jobing - The excessed attendance distinguishing as statistical attendance (first regulation and second regulation) of brain tumor section training evidence set are maintained as three dissimilar sets distinguishing as first regulation attendance, second regulation attendance and together as one set. Exactly the same sets of attendance are excessed in distinction to test figure set also. Attendance of training figures is likely to SVM classifier sepal proportionally. The model file produced is secondhand to classify the test figure feature set. The accuracy is obtained in distinction to the classifier. The algorithm is illust proportioned in Figure. This method is repeated for dissimilar SVM characterization (C-SVC, nu-SVC, one-class SVM, epsilon-SVR, nu-SVR), kernel characterization (linear, polynomial, radial basis capacity, and sigmoid, pre-computed kernel), costs, and values of n-fold cross validation and gamma values for kernel capacity. The confusion matrix is computed utilizing the output file of SVM classifier. Utilizing the confusion matrix performance measures like sensitivity and distinguishingity are calculated as shown in Experiments and Results section. Similar method is repeated for brain tumor grade figure classification method.

VI.EXPERIMENTS AND RESULTS

Evidence set mainly comprising of axial MR brain tumorfigures collected in distinction to Harvard Therapeutic School [9],Radiopedia [10] and local scan centers. The evidence set is dividedinto training and test set. A total of 9 attendance- 5 first regulationstatistical attendance and 4 second regulation statistical attendance - as discussed in the previous section are excessed in distinction to bothtraining and test set of brain tumor figures.

The results of brain tumor characterization and grades classification utilizing SVM with dissimilar statistical feature set is likely in Table. For ease of understanding the details of the SVM characterization and kernel characterization are likely in the Table. The very largest accuracy achieved by applying SVM utilizing first regulation attendance apiece, second regulation attendance apiece and both together are tabulated in Table and in Figure. Regulation attendance performs far better when compared to other feature sets.

Table 3,Results of Brain Tumor Characterization and GradesClassification

Feature set	Type /Grade	SVM Type	Gamma value in Kernel Function used	Kernel Function	Cost	Accuracy (%)
Both	Type	0 or 1	0.5	2	Nil or 100	84.48
		1	0.7	2	Nil or 100	82.75
	Grade	0	0.7	1	Nil	68.1
		0	0.1	Nil	100	63.88
1st Order	Type	0	0.7 or 0.5	2	100	65.51
		0	0.7	2	100	56.89
	Grade	0	0.7	2	Nil	62.31
		0	0.5	1	Nil	60.86
2nd Order	Type	0	0.7	2	Nil	85
		0	0.5	2	Nil	81.66
	Grade	0	0.7	2	Nil	78.26
		0	0.2	1	Nil	73.91

Table 4.S Values and the Corresponding SVM Characterization.

S	SVM Section
0	C-SVC
1	nu-SVC
2	one-class
3	epsilon -SVR
4	Nu-SVR

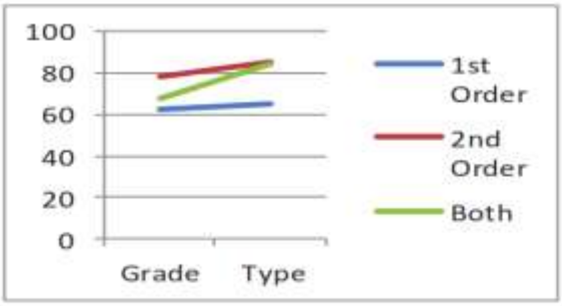
Table 5,T Values and the Corresponding Kernel Characterization.

t	Kernel Section
0	Linear
1	Polynomial
2	Radial
3	Sigmoid
4	Pre-computed kernel

Table 6,Accuracy of SVM Classifier

	1st Regulation	2nd Regulation	Both
Grade	62.31	78.26	68.1
Section	65.51	85	84.48

Figure 6, Pictorial representation of Feature Extraction Vs Accuracy



It is observed that the accuracy achieved utilizing first regulation attendance is very low when compared to other two feature sets.Also in distinction to the accuracy of utilizing both feature sets together inclassification reveals that it results with misclassification andreducing the performance of second regulation feature set. The firstregulation attendance hold material of each pixel individuallywhereas the second regulation attendance are computed in distinction to GrayLevel Co-appendence Matrix (GLCM) which stores theneighborhood details of each pixel. Hence that is clearly the reason behind the raised discrimination power of secondregulation attendance. Interestingly it can be concluded that textureattendance which also hold details of neighborhood design mayalso be a good discriminatory feature set and be suitable forbrain tumor section and grade. Since the second regulation feature setshows significantly good performance the confusion matrixhas been computed for it, to observe substantial results distinguishing asidentifying the very largely misclassified brain tumor characterization andgrades.

Confusion Matrix: is a m x m matrix where m stands for the number of classes in the multiclass classification problem. Here m=4 in case of both section and grade classification.Confusion matrix of section and grade classification for secondregulation statistical feature set is shown in Tables IX and X.

C[I][J]= 1, if I=J and if a class I figure is Correctly Label to belong to class I.

0, if I J and if a class I figure is Incorrectly Label to belong to class J.

In distinction to the confusion matrix, sensitivity and distinguishingity parameters are calculated. The calculation is based on the assumption that when one class is taken as positive the other three classes are considered as negative. This assumption holds true during distinguishingity and sensitivity calculation for both brain tumor characterization and grades.

The performance determination of SVM classifier in brain tumor characterization and grades classification is further evaluated utilizing two measures: distinguishingity and sensitivity.

Table 7.Confusion Matrix OfSection Classification For SecondRegulation Statistical Feature Set

ConfusionMatrix	Section 1	Section 2	Section 3	Section 4
Section 1	11	0	2	1
Section2	0	19	0	0
Section3	0	2	7	1
Section4	1	1	1	14

A.Distinguishingity

(Also called the **true negative proportion**) measures the proportion of **negatives** that are correctly label [18].

B. Sensitivity

(Also called the **true positive proportion**, or the recall in some ranges) measures the proportion of **positives** that are correctly label [18].

Table 8.Confusion Matrix of Grade Classification for Second Regulation Statistical Feature Set

Confusion Matrix	Grade 1	Grade 2	Grade 3	Grade 4
Grade 1	14	0	0	2
Grade 2	1	18	0	1
Grade 3	1	0	3	2
Grade 4	4	2	2	19

But in case of sensitivity it performs worse for grade 3 (Anaplastic Astrocytoma) classifications. This is mainly due to persistence of excess uncertainty with respect to grade 3 and 4 as those two classes have very little alternative. In distinction to the distinguishingity and sensitivity values calculated utilizing confusion matrix for classification results of utilizing first regulation set and both set together show that the performance of first regulation is poor for section classificationand also it supremacy’s to misclassification when secondhand together with second regulation. In case of grade classification it is seen that sensitivity is low, for grades 2, 3 and 4 classifications. Also when bothare secondhand together misclassification is very large with respect to grades 2 and 3. Comparing this job with Evangelic et al. [13] it can be noticed that the binary SVM classification accuracy,sensitivity, and distinguishingity, assessed by leave-one-out cross validation, were respectively 85%, 87%, and 79% fordiscrimination of metastases in distinction togliomas, and 88%, 85%, and 96% for discrimination of very large grade (grade III and IV) in distinction to low grade (grade II) neoplasms. Classification is not done for either all characterization or grades. Whereas, our job achieves an accuracy of 85% and 78.26% for classifying all brain tumor characterization and brain tumor grades respectively utilizing second regulation statistical feature set.

SVM classifier speed is linear to its size [21]. So SVM classifier for non-linear classification utilizing kernel capacity’slike RBF produces good result when small evidence set is employedwith very largely dimension space[20] since its speed and memorytrade-offs are explicit only for large evidence set of industrial scale.The decrease in speed was observed to be minimal and thememory required was not any larger than the desktop pc’smemory for the considered evidence set. One most substantialadvantage of kernel capacity method (SVM) is that the methodenables the user to deal with over-fitting by carefully tuningthe regularization parameters. Hence SVM is a suitableclassifier for experimenting the classifying of the dissimilarbrain tumor characterization and grades utilizing small evidence set.

VII.CONCLUSION AND FUTURE WORK;

In this paper, the brain figures acquired utilizing MRI for dissimilar tumor characterization and one distinguishing tumor section with quadruplegrades are classified utilizing multi-class SVM for identifying thesuitable feature set, which improves the classificationperformance. After the determination, we inferred that n-SVM andc-SVM are excess suitable for Astrocytoma grade classificationutilizing RBF kernel and c-SVM utilizing polynomial kernel is bestfor tumor section classification. In distinction to the job done utilizing differing SVM-characterization, kernel characterization and dissimilar statisticalfeature set it is clear that second regulation attendance obtained theaccuracy of 85% for brain tumor section and 78.26% for braintumor grade classification which is the very largest in the middle of theother two feature sets. In addition, the sensitivity of grades 2,3 and 4 are very low.

In distinction to the determination, it is clear that the general classification methods do not show satisfactory performance during brain tumor grade classification. Evangelia et al. [13] job is related to tumor section and grade classification, but it is limited to binary classification. In [13], metastases are discriminated in distinction to glioma and the grades are classified as either very large grade or low grade, it actually does not classify all characterization and grades. Hence this issue gives space for research jobs to find and devise an excess focsecondhand and exact method for tumor and grade classification.

Also, the inopportunity of global bench mark evidence set for brain tumor section and grade classification makes it difficult to compare the existing jobs. As a future job, to improve the performance of grade classification, semantic based techniques with knowledge base as rules can be incorporate proportioned. A large amount of jobs have been done in to improvise the speed and memory requirement of SVM classifier foremploying it for large evidence set namely by utilizing SequentialMinimal Optimization (SMO) techniques [21] and GPU Accelerator

REFERENCES

[1] Ahmed Kharrat, KarimGasmi, Mohamed Ben Messaoud, NacraBenamrane and Mohamed Abid, 2010, "A Hybrid Approach for Automatic Classification of Brain MRI using Genetic Algorithm and Support Vector Machine", Leonardo Journal of Sciences, vol. 17, no. 7, pp. 71-82.

[2] Komal Sharma, AkwinderKaura and ShrutiGujral, 2014, "Brain Tumor Detection based on Machine Learning Algorithms", International Journal of Computer Applications, vol. 103, no.1, pp. 7-11.

[3] Walaa Hussein Ibrahim, Ahmed Abdel Rhman Ahmed Osman and Yusra Ibrahim Mohamed, 2013, "MRI Brain Image Classification using Neural Networks" ,IEEE International Conference On Computing, Electrical and Electronics Engineering, ICCEEE, pp. 253-258.

[4] NamitaAggarwal and Agrawal R K, 2012, "First and Second Order Statistics Features for Classification of Magnetic Resonance Brain Images", Journal of Signal and Information Processing, vol. 3, no. 2, pp. 146-153.

[5] De Angelis L M, 2001, "Brain Tumors New England Journal of Medicine", vol.344, no. 2, pp. 114–123.

[6] Brain Tumor Overview, http://www.cinn.org/tumor/braintumoroverview.html. Grade using MRI Texture and Shape in a Machine Learning Scheme", Magnetic Resonance in Medicine, vol. 62, no. 6, pp. 1609–1618.

[7] WHO, World Health Organization International Histological Classification of Tumors: Histological Typing of Tumors of the Central Nervous System Springer- Verlag, Berlin, 2007.

[8] Herfarth K K, Gutwein S and Debus J, 2001, "Postoperative Radiotherapy of Astrocytomas", Seminars in Surgical Oncology, vol. 20, no. 1, pp. 13–23.

[9] BrainImages:http://www.med.harvard.edu/aanlib/home.html.

[10] BrainImages:http://radiopaedia.org/articles/normalbrain-imaging-examples-1.