# Experimental Approaches for Detection of Brain Tumor Grade Using Svm Classification

**V Ramakrishna Sajja, Gnaneswara Rao Nitta**

***ABSTRACT--- Brain tumor detection is an urgent assignment for doctors. Cerebrum tumor grows quickly and average volume will be doubled in only twenty days. If it is not diagnosed carefully, the life time of the patient will not be the greater part a year. Such tumors can quickly prompt passing. Thus, a programmed framework is required for mind tumor identification at a beginning period. In this paper, a computerized strategy is proposed to effectively separate amongst harmful and cancerous free Magnetic Resonance Image (MRI) of the mind. Diverse systems are imposed to isolate tumor. At that point feature set has been considered at each tumor region utilizing Intensity, shape and surface. By then, a popular classification technique called Support Vector Machine (SVM) is imposed by various cross validations on the features set to look at the accuracy of structure introduced in this paper. The new technique approved on a standard dataset, BRATS. The strategy accomplished with average accuracy of 98.2%, area under curve is 0.98, sensitivity of 92.8% and specificity of 98.5%. This method can be utilized to distinguish the brain tumor with much accuracy when contrasted with earlier techniques proposed.***

***Keywords: Brain tumor, pre processing, Segmentation, K-Means, Morphological operations, Feature Extraction, Classification, and Support Vector Machine.***

## 1. INTRODUCTION

Cerebrum tumor is called an unordinary development of the cells in the brain. On the off chance that tumor isn't analyzed appropriately then it generally spread in the mind which prompts lose the life[1].

Around fifteen thousand deaths in every year are happening due to the malignant tumors which are the risky types of tumor. In spite of wide exertions in explore over various decades, the center Overall Life-time (OLT) will be fifteen months just for the Glioblastoma Multiforme (GBM) , dangerous glioma [2]. Because of seriousness stage, the cerebrum tumor has been isolated into various evaluations. At stage1 minimum risky tumor is ordinarily identified with drawn out survival. When it is seen through a magnifying instrument, they develop step by step and for all intents and purposes have a standard appearance. Dignosis by means of medical procedure may be recommended for such kind of tumor review. Ganglioglioma, gangliocytoma and pilocytic astrocytoma are instances of stage1 brain tumor. The tumor which develops gradually and looks irregular under a tiny instrument is treated as stage2 brain tumor. A tumor which is hardly distributed to adjacent tissues and replicates multiple times is known as high grade tumor [3]. The tumor which is dangerous however by and large is called stage3 brain tumor; there is certifiably not a noteworthy difference between stage2 and stage3 tumors. This tumor tends to often rehash as stage4. Stage4 is the most extreme threatening tumor. It copies rapidly having an interesting look when found in the minute tool and viably develops into the adjacent tissues of the cerebrum bringing about the presence of new vessels. Such tumor cells have groups of dead cells in their middles. GBM is an example of stage4 tumor [4].

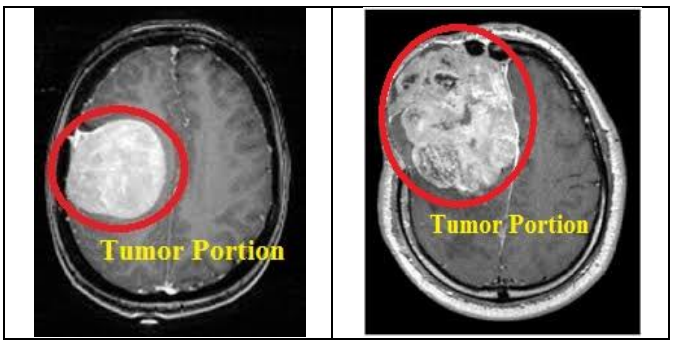


**Fig. 1: Brain Tumor**

Tumors can be detected by rich techniques of image processing. Segmentation of images is one among them. The objective of image division is to divide an image into different partitions thus discovering states of the partitions [5– 6]. The brain life structure will be examined by either Computed Tomography (CT) or Magnetic Resonance Imaging (MRI). CT scan is less effective when compared with MRI scan due to the utilization of radiation [7]. Just a single sort of MRI can't give entire data identified with typical tissues because it consists of different biologic tissues. Joining distinctive correlative data can overhaul the divided locale of tumors. Highlights of MR pictures used for division involve three pictures of weighted (Proton Density (PD), T1 and T2) for each cut axial. The strategies of segmentation have been completely powerful particularly in the development phases of contaminated tissues [8– 10].

Principle commitments of this examination incorporate the accompanying:

- ❖ Proposed a programmed strategy to classify and detect cerebrum tumor at lesion level. Preprocessing, segmentation, feature extraction and classification are the stages included in proposed methodology.
- ❖ In preprocessing stage, candidate lesions can be segmented by applying various techniques. Thus shape, intensity and texture oriented features set are connected on every candidate lesion.

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**V Ramakrishna Sajja,** Department of Computer Science and Engineering, VFSTR deemed to be University, Vadlamudi, Guntur Dt, Andhra Pradesh, INDIA. (E-mail: vramakrishnasajja@gmail.com)

**Gnaneswara Rao Nitta,** Department of Computer Science and Engineering, VFSTR deemed to be University, Vadlamudi, Guntur Dt, Andhra Pradesh, INDIA. (E-mail: gnani.nitta@gmail.com)

- At last, more relevant classification strategy is identified by doing various tests on the chosen features set. For this reason, Support Vector Machine (SVM) with various cross validations is applied. Three kernels of SVM are tried i.e., Gaussian, Cubic and linear kernel functions. The technique is tried on BRATS datasets in light of the evaluation parameters, for example, Accuracy (ACC) and Area Under Curve (AUC).

The paper is organized as the following. Literature work for tumor identification is described at section II, Proposed technique steps are depicted at section III and outcomes after the performance assessment of recommended strategy are illustrated in Section IV.

## 2. LITERATURE WORK

Segmentation of image is treated as a basic examination subject in medical field. Numerous examiners have introduced image segmentation strategies and diverse frameworks for cerebrum tumor identification; some are depicted here.

In the process of tumor segmentation, morphological operators can be utilized [11]. In the identification of cerebrum tumor, Non-negative Matrix Factorization (NMF) is used [12]. Gray Matter (GM), Cerebrospinal Fluid (CSF) and White Matter (WM) tissues are identified by imposing the neuro-fuzzy technique [13]. Tumor and non-tumor portions of brain are differentiated by using mechanized Bayesian regularization with feed forward multilayer neural system and it is identified by using Piece Wise-Triangular-Prism-Surface-Area (PTPSA) [14] and Fuzzy C-Means (FCM) [15]. The treatment of tumor can be recognized by K-means clustering technique [16]. The recommended strategy involves three phases, for example, fine grain localization, K-means clustering and guided grid based local standard deviation of coarse. There are two sections in separation of cerebrum tumor. One section contains ordinary cells of the cerebrum consists of WM, GM and CSF. The second section involves contaminated tissues. Area of intrigue is isolated by segmentation strategy. Image fusion strategy gives great outcomes in the combination of port images [17]. The images of Positron Emission Tomography (PET) datasets are inspected by Spatial Fuzzy C-means (SFCM) clustering method [18]. Tumors are recognized by using MRI with FCM technique [19]. Fast Fourier transforms, progressed morphological strategy and Thresholding are utilized for the identification of the contaminated cells and it is tried on T2 weighted images [20]. Cerebrum lesion is recognized by popular method Histogram-based Gravitational Optimization Algorithm (HGOA) with an accuracy of 91.5% [21]. Lesion area is isolated by FCM segmentation strategy [22] and K-means clustering method [23] and it is watched that FCM is inferior to K-Means. To segregate non cancerous and cancerous tissues, Gabor wavelet features are tried on few classifiers [24]. Cerebrum tumors areidentified by the combination of KSVM and Gray Level Co-Occurrence Matrix (GLCM) [25].

In this paper, a programmed system is introduced for the segmentation and classification of cerebrum pathology at lesion level.

By applying K-means clustering approach at lesion level, It is classified as benign also called as stage 1, 2 (low-level tumor) and malignant also called as stage 3, 4 (high-level tumor). Here intensity, texture and shape based features are utilized for classification. In the classification step, three portions of the geometrical family are tried to examine the accuracy of introduced strategy.

## 3. PROPOSED METHODOLOGY

Cerebrum tumor at the lesion level is identified by implementation of proposed methodology. Anticipated technique has been examined with the help of Magnetic Resonance Images. Contaminated cell identification in MRI is much capable due to its low radiation, spatial resolution and high contrast and. Magnetic resonance images provide data connected to position and volume of a cerebrum tumor but those pictures cannot able to detect the tumor stage. Clinicians could not able to detect the tumors with in less time and that process was so painful to patients. This difficulty was addressed by proposed system which improves the tumor identification capability of MR Pictures. As the proposed technique is able to classify the cerebrum tumors, biopsy is not required in initial stage. The proposed method consists of four important levels those are preprocessing, segmentation, feature extraction and classification. In preprocessing, first skull part is removed by Thresholding, then image will be converted into gray scale and finally Gaussian filter is applied to remove noise. In segmentation, various techniques are imposed to extract the target portion. Now texture, intensity, and shape features are retrieved for every patient lesion. Now classification is applied to detect tumor grade be means of various kernels of SVM. The mechanical anticipated technique useful in early identification of tumor. Figure 2 describes the important levels of anticipated technique.

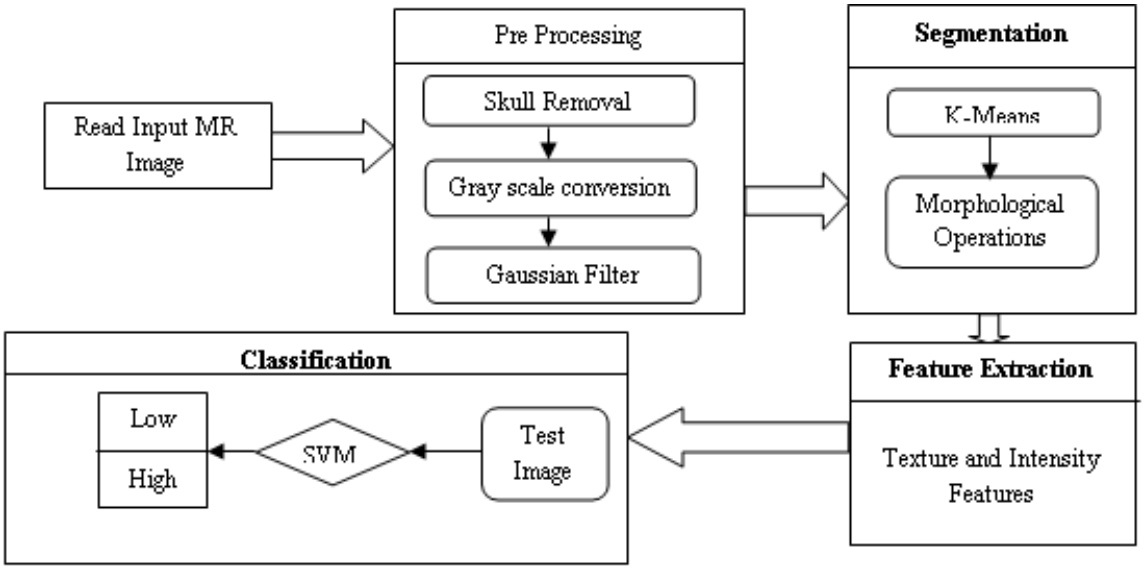


**Fig.2: Proposed Frame work**

*3.1. Preprocessing*

In the process of cerebrum tumors recognition, information has been procured from freely available datasets that comprise of irregular MRIs. The irregularities in MRIs have to be wiped out, in this way, preprocessing is imposed. The time complexity is raised when background of image is utilized due to unnecessary data in the image. So skull, eyes, back-ground and scalps are removed and excluded in the area of intrigue. Brain Surface Extractor (BSE) technique has been applied to remove cerebrum followed by skull. BSE is utilized to recognize the edges and do morphological activities, for example, erosion. It likewise do cleanup surface and image masking. Fig. 3 demonstrates about skull expulsion process.

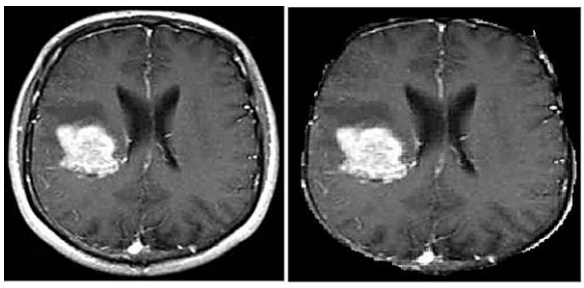


**Fig. 3: (a) MRI Image as Input (b) Removal of skull**

At that point the image of input f(x, y) has been changed over into gray scale. 5 ×5 Gaussian filter has been adopted for smoothing and to remove unwanted information appeared in Figure 4.In Eq. (1) , G(x,y) speaks to Gaussian filter and σ demonstrates the standard deviation of the Gaussian dispersion.

$$xG(X,Y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

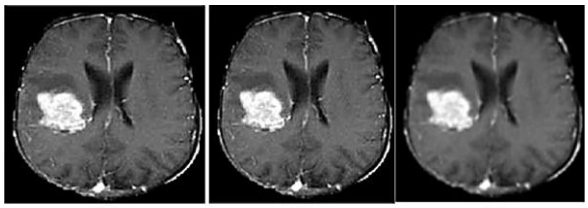


**Fig. 4: (a) Removal of skull (b) Gray Scale Image (C) Smoothing Image**

*3.2 Segmentation:*

At that point unsupervised learning calculation is connected, for example, k-means [26] to tackle the issue into partitions. In the new strategy, three partitions have been utilized to classify the information on the grounds that popular outcomes have been accomplished in partition 3. Expanding the span of the group won't enhance the identification time; instead process completing time is expanded. K focuses have characterized at each partition. K focuses have put in craftiness way in light of the fact that distinctive outcomes show up in various areas. In this way, these focuses are found inaccessible far from each other. In the last advance, a circle is made in which well ordered variety happens in K focuses until the point when no further variety is finished. The district of intrigue is chosen in the required bunch. $X_i - V_j$ speaks to the Euclidean separation between $X_i$ and $V_j$, $C_i$ signifies information focuses number in the $i^{th}$ bunch and c indicates add up to group focuses. The procedure of K-means partitions is appeared in Figure 5. In partition 1, the proportion of healthy pixels is expanded. In partition 2, the limit of contaminated pixels is gotten and targeted pixels have been accomplished in partition 3. Cluster quality can be estimated by Silhouette coefficient [27]

$$G(x,y) = \sum_{i=1}^{c}\sum_{j=1}^{c_i}\left(\|X_i - V_j\|\right)^2 \quad (2)$$


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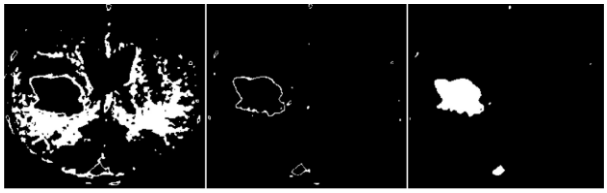


**Fig. 5: Outcomes of K-means clustering (a) Partition 1 (b) Partition 2 (c) Partition 3**

Morphological operator like erosion has been adopted on g(x, y) to acquire the required patient tumors. This process uses binary image and Eq. (3) to eliminate unwanted pixels.

$$G(x,y) \ominus B = \{Z \in E \mid B_z \subseteq g(x,y)\} \quad (3)$$

Circle formed organizing component (B) with radius of 4 is utilized. E denotes whole number network and $B_z$ is B by means of vector Z interpretation. Figure 6 indicates impact of erosion on partitioned picture.

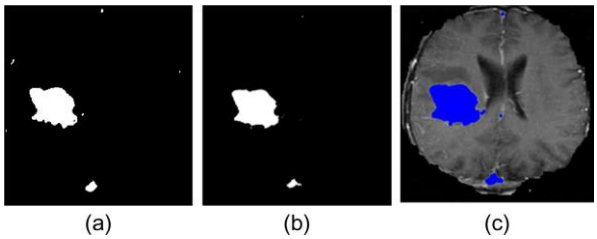


**Fig. 6: Results of erosion on segmented image**

Tumor oriented pixels are identified truthfully by morphological operators. If such a technique is not utilized, low stage tumor is appeared as high stage tumor due to the raising rate of tumor pixels which are originally non-tumor pixels. Hence morphological tasks, for example, erosion and dilation are adopted for the right location of the tumor. In spite of the fact that erosion evacuates additional pixels and lessens the FPR, it doesn't kill real tumor pixels. Regardless of whether any contaminated pixels are left, a dilation task is adopted to retrieve those pixels. Identification of cerebrum tumor at lesion level is said underneath in Algorithm 1.

| **Algorithm 1: Identification of cerebrum tumor at lesion level** |
|---|
| Step1: Read MRI image as input. |
| Step2: Apply Thresholding to remove skull part. |
| Step3: Apply K – means algorithm to extract lesion. |
| Step4: Apply erosion on segmented part to remove extra pixels and reduces FPR. |
| Step5: Apply dilation on segmented part to recover missed pixels. |
| Step6: Write output MRI image. |

*3.3 Feature Extraction:*

It is the way toward gathering higher level data of a picture, for example, shape, surface, shading, what's more, differentiate. In fact, surface examination is an imperative parameter of human visual observation and machine learning framework.It is utilized successfully to enhance the precision of analysis framework by choosing noticeable highlights. Haralick et al. [32] presented a standout amongst the most broadly utilized picture investigation utilizations of Gray Level Co occurrence Matrix (GLCM) what's more, surface element. This system pursues two stages for include extraction from the therapeutic pictures. In the initial step, the GLCM is processed, and in the other advance, the surface highlights dependent on the GLCM are computed. Due to the perplexing structure of expanded tissues such asWM,GM, and CSF in the cerebrum MR pictures, extraction of pertinent highlights is a fundamental assignment. Textural discoveries and examination could enhance the conclusion, distinctive phases of the (tumor arranging), and treatment reaction appraisal. The insights highlight recipe for a portion of the valuable highlights is recorded underneath.

**Table 1: Feature set to be extracted for classifying tumor.**

| Sl. No. | Feature | Formulae | Description |
|---|---|---|---|
| 1 | Energy | $\sum_{i,j=0}^{N-1} {P_{i,j}}^2$ | Squared elements addition in GLCM. |
| 2 | Homogeneity | $\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$ | Estimates the likeliness of the division of pieces within the GLCM to the GLCM diagonal. |
| 3 | Contrast | $\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2)$ | Estimates the nearby differences in GLCM. |
| 4 | Correlation | $\sum_{i,j=0}^{N-1} P_{i,j}[\frac{(i-u_i)(j-u_j)}{\sqrt{(\sigma^2{}_i)(\sigma^2{}_j)}}]$ | Estimates the combined probability happening of the specific pixel joints. |

*3.4 Classification:*

A more relevant classification strategy is identified by doing various tests on the chosen features set. For this reason, Support Vector Machine (SVM) with various cross validations is applied. Three kernels of SVM are tried i.e., Gaussian, Cubic and linear kernel functions.

*3.4.1 Support Vector Machine (SVM):*

Tumors are classified by means of SVM with the support of features vector definition. It is a important

classifier in factual learning area. It utilizes kernel technique for dealing with the high dimensional information. It uses regularization parameter to free from local, overfitting and global minima. The fundamental thought in this technique utilizes support vector which leads a hyperplane by expanding edges among the classes. Considered an arrangement of models $\{(x_1, y_1), (x_2, y_2) \ldots (x_r, y_r)\}$, SVM is utilized to discover the problem solving of advancement issue as given in Eqs. (4)– (5).

$$\text{Minimize: } \frac{<W.W>}{2} + C\sum_{i=1}^{r} \in_i \quad (4)$$

$$\text{Subject to: } y_i(< w.x_i > + b) \geq 1 - \in_i, i = 1,2, \ldots \ldots, r \quad (5)$$

Where $x_i \in R^r$ is a r dimensional space and $y_i = \pm 1$, where 1 and −1 speak to malignant and noncancerous cells individually. C speaks to the arched enhancement. Other than straight grouping, SVM likewise performs nonlinear order with high accuracy by utilizing part traps. In such manner, support vector machine changes features set from a low to high dimension. Three kernels of SVM i.e., Gaussian, Cubic and linear kernel functions are adopted in the new strategy to increase accuracy and decrease False Positive Rate. Such of these kernels are made reference to utilizing Eqs. (6)– (8) .

$$Linear\ Kernel\ K(X_i, X_j) = X_i^T . X_j \quad (6)$$

$$Radial - Basis\ Function\ K(X_i, X_j) = \exp(-\frac{\|X_i - X_j\|^2}{2\sigma^2} \quad (7)$$

$$Cubic\ Kernel\ K(X_i, X_j) = \quad (8)$$

A classifier with better hypothesis is accomplished utilizing cross validation procedure. In cross validation strategy, 30, 25, 20, 15, 10 and 5 fold is chosen for classification. 30 fold implies entire information is arranged into 30 partitions, amongthose one partition is used for testing and rest of partitions have been taken for training. Likewise, in the following stage, 25 fold intends to isolate the entire information into twenty five partitions with the end goal that one partition is for testing use and staying twenty four are utilized for training. This methodology proceeds for the 20, 15, 10 and 5 fold in various cycles.

## 4. EXPERIMENTAL RESULTS

We have taken data set from popular BRATS database. We have downloaded 280 MRI images, In which 100 are normal images and 180 are abnormal images.

### *4.1 Experimentation results and discussion*

Tumor detection at lesion level has been done on BRATS datasets and it is assessed in the exhibited technique. This methodology and its outcomes are contrasted with ground truth explanation that is freely available. AUC and ACC of proposed strategy are collected from standard datasets. Those are made reference to in tables 2– 4. Equations (9)– (15) are utilized to acquire specificity, sensitivity, FPR, PPV, False Negative Rate (FNR), ACC and AUC individually. False Positive (FP) speaks to the wrong recognition of non-tumor pixels. Lesion pixels that are not recognized by the introduced calculation are denoted as False Negative (FN). Sum of lesion pixels demonstrate True Positive (TP). True Negative (TN) indicates the healthy pixels. True positive rate signifies TPR.

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

$$AUC = \int_{\propto}^{-\propto} TPR(T)FPR'(T)dT \quad (10)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (11)$$

$$Specificity = \frac{TN}{TN+FP} \quad (12)$$

$$PPV = \frac{TP}{TP+FP} \quad (13)$$

$$FPR = 1 - Specificity \quad (14)$$

$$FNR = 1 - Sensitivity \quad (15)$$

The tumor in MRI is effectively identified by recommended strategy. The general execution of new framework is enhanced when contrasted with past techniques on the grounds that exact characterization lies on the partition of lesions and feature extraction. Tumor at lesion level is accurately partitioned by introduced strategy. The retrieved feature set comprises of texture, intensity and shape features which assist in doing classification. Thus, when the tumor is identified by means of classifier at tumor level, the tested picture is named as stage 1, 2 additionally called benign (low stage tumor) and stage 3, 4 called malignant (high stage tumor) as specified in the Tables 2 – 4.

**Table 2: Classifying the tumorous and non-tumorous results by utilizing linear kernel.**

| Cross Validation | Specificity | False Positive Rate | Sensitivity | False Negative Rate | Accuracy | Area Under Curve |
|---|---|---|---|---|---|---|
| 30 fold | 100 | 0.000 | 92.4 | 0.076 | 98.8 | 1 |
| 25 fold | 98.0 | 0.020 | 98.5 | 0.015 | 99.6 | 1 |
| 20 fold | 96.5 | 0.035 | 98.7 | 0.013 | 99.1 | 0.99 |
| 15 fold | 97.0 | 0.030 | 90.3 | 0.097 | 96.9 | 0.94 |
| 10 fold | 99.5 | 0.005 | 89.4 | 0.106 | 97.1 | 0.98 |
| 5 fold | 100 | 0.000 | 87.5 | 0.125 | 97.8 | 0.97 |

**Table 3: Classifying the tumorous and non-tumorous results by utilizing Gaussian kernel.**

| Cross Validation | Specificity | False Positive Rate | Sensitivity | False Negative Rate | Accuracy | Area Under Curve |
|---|---|---|---|---|---|---|
| 30 fold | 94.8 | 0.052 | 87.3 | 0.127 | 93.4 | 0.98 |
| 25 fold | 84.2 | 0.158 | 87.3 | 0.127 | 97.8 | 0.93 |
| 20 fold | 77.2 | 0.228 | 92.0 | 0.080 | 81.3 | 0.92 |
| 15 fold | 67.3 | 0.327 | 92.0 | 0.080 | 75.2 | 0.87 |
| 10 fold | 79.0 | 0.210 | 02.0 | 0.980 | 83.2 | 0.90 |
| 5 fold | 70.5 | 0.295 | 90.0 | 0.100 | 78.7 | 0.91 |

**Table 4: Classifying the tumorous and non-tumorous results by utilizing cubic kernel.**

| Cross Validation | Specificity | FalsePositive Rate | Sensitivity | False Negative Rate | Accuracy | Area Under Curve |
|---|---|---|---|---|---|---|
| 30 fold | 95.8 | 0.042 | 95.1 | 0.049 | 96.8 | 0.94 |
| 25 fold | 97.3 | 0.027 | 95.4 | 0.046 | 95.5 | 0.95 |
| 20 fold | 100 | 0.000 | 97.2 | 0.028 | 98.7 | 0.98 |
| 15 fold | 97.8 | 0.022 | 96.8 | 0.032 | 97.4 | 0.94 |
| 10 fold | 100 | 0.000 | 72.4 | 0.276 | 87.0 | 1 |
| 5 fold | 97.8 | 0.022 | 81.0 | 0.190 | 90.0 | 0.98 |

While on account of BRATS dataset got is maximum of 98.2% accuracy, 0.98 area under curve, 92.8% sensitivity and 98.5% specificity at the linear part on average of all cross validations. Note that AUC (in light of ROC) and accuracy are not a similar idea. So as accuracy is looked at on one cut point, it changes for various such cut focuses. Results of new method contrast with literature are depicted in table 5.

**Table 5: Introduced strategy comparison with earlier strategies**

| Existing methods | Year | Results |
|---|---|---|
| Proposed Method | 2018 | 98.2% Accuracy |
| SVM + Texture Features [28] | 2017 | 97.1% Accuracy |
| Hybrid Clustering [23] | 2015 | 95.06% Accuracy |
| Gravitational optimization [21] | 2014 | 91.50% Accuracy |
| Artificial Intelligence [22] | 2016 | 91.00% Accuracy |
| Advanced Morphological techniques [20] | 2016 | 89.20% Accuracy |
| Gabor Wavelets Vs Statistical Features [24] | 2015 | 79.3% Accuracy |

## 5. CONCLUSION

In this paper, cerebrum malignant growth using Magnetic Resonance Imaging (MRI) is identified by a computerized framework which has been introduced through the phases of preprocessing, segmentation, feature extraction and classification. Examining of introduced strategy is accomplished at lesion levels for point by point appraisal. Execution estimates, for example, accuracy (ACC) and area under curve (AUC) are utilized for the assessment of recommended technique on openly accessible and one nearby dataset. The recommended approach can be utilized to build tumor discovery technique at a beginning time before the intricacies stage. Results of tests exhibit the outperformance of displayed philosophy when contrasted with earlier strategies. This work will be useful in analyzing the cerebrum tumors decisively and precisely.

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