

Texture based localization of a brain tumor from MR-images by using a machine learning approach[☆]



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ARTICLE INFO

Keywords:

Localization
Superpixel
Texton-map
AdaBoostM1
RusBoost
Random forest
Support vector machine

ABSTRACT

In this paper, a machine learning approach was used for brain tumour localization on FLAIR scans of magnetic resonance images (MRI). The multi-modal brain images dataset (BraTs 2012) was used, that is a skull stripped and co-registered. In order to remove the noise, bilateral filtering is applied and then texton-map images are created by using the Gabor filter bank. From the texton-map, the image is segmented out into superpixel and then the low-level features are extracted: the first order intensity statistical features and also calculates the histogram level of texton-map at each superpixel level. There is a significant contribution here that the low features are not too much significant for the localization of brain tumour from MR images, but we have to make them meaningful by integrating features with the texton-map images at the region level approach. Then these features which are provided later to classifier for the prediction of three classes: background, tumour and non-tumour region, and used the labels for computation of two different areas (i.e. complete tumour and non-tumour). A Leave-one-out (LOOCV) cross validation technique is applied and achieves the dice overlap score of 88% for the whole tumour area localization, which is similar to the declared score in MICCAI BraTS challenge. This brain tumour localization approach using the textonmap image based on superpixel features illustrates the equivalent performance with other contemporary techniques. Recently, medical hypothesis generation by using autonomous computer based systems in disease diagnosis have given the great contribution in medical diagnosis.

Introduction

Automatic diagnosis and localization of a brain tumour from MR scans are crucial decrease the rate of casualties. Due to this, it has been becoming an active area of research for the past few decades. Because of the complex structure and interconnected tissues, it is challenging to cure a brain tumour. The robustness and efficiency of the existing brain tumour localization techniques, still faces many challenges and need to improve them. Tumour localization and classification is a difficult problem as tumours vary in appearance, structure and position/location. Because of the complex structure, it is a complicated task to completely localize and classify a brain tumour from MRI scans. In MRI, Multi- Modality is a feature of capturing multiple images which can supply comprehensive details of the brain to classify brain tumour efficiently [1] and acquired substantial interest in last few decades. Fig. 1

shows various MR modalities. The significance of each modality of MR scans has explored in many studies. In recent times, researchers have explored different methods for these modalities of MR scans to improve the accuracy of tumour localization and classification. Medical and hypothesis systems works for the advancement of technological scientific methods in various fields like tele transportation, economics, communications, and surveillance. An important thing that consider in these machine vision based systems is to match or surpass human vision performance. Computer vision and machine learning approaches have validly operated with multi-parametric modalities of (i.e. T1, T2, T1C and FLAIR) MR scan [2]. The vision-based ML approaches highly depend on the quality of extracted features from the images. Individually an image is classified by its feature vector [3]. Regional level based features pipeline has explored by using the Low-level intensity statistical, texton map histogram level on the brain tumour benchmark

* Machine learning based algorithm for brain tumor localization.

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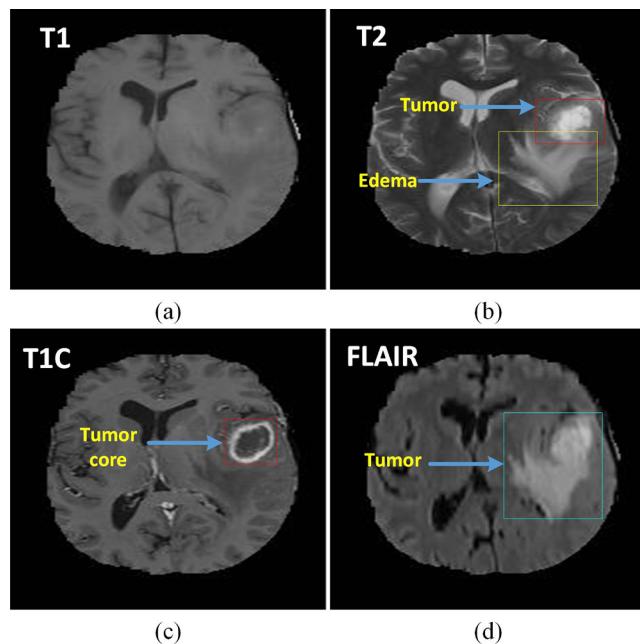


Fig. 1. Multi-parametric MR scans of brain modalities showing a) T1, b) T2, c) T1C (T1 Contrast-enhanced) and d) Fluid attenuated inversion recovery (FLAIR).

dataset [4]. In this study, we aimed at building and validating a computerized technique for a FLAIR, single modality that can promptly translate for the clinical use. To the extent of our knowledge, the proposed pipeline in such a manner to process the images at first in texture-map and then extract the superpixel based low-level features have not yet explored on FLAIR modalities of MR scans for brain tumour localization. In this paper, we investigate this proposed pipeline of extracting regional level features from texture-map images as well as miscellaneous machine learning techniques.

In this paper, FLAIR modality of MR scans are used for localization of whole brain (lesion or tumour) region. The following contributions are made:

1. Creating texture-map images and texture maps,
2. Extracting low level features are extracted in order to predict tumour region,
3. Exploring the supervised based classifiers are explored for brain tumour localization.

The rest of the paper is composed in the following order: relevant work is revised in Section “Relevant work”, Section “Proposed method” describes the proposed work, Section “Feature extraction” feature extraction Section “Feature selection” feature selection Section “Class balancing” class balancing Section “Classification” classification Section “Experimental setup” experimental setup Section “Discussion” discussion and conclusion are described in Section “Conclusion”.

Relevant work

The computerized localization of brain tumour is a complex task, because of its inhomogeneous intensities and unclear boundaries of a tumour and the brain region within the voxel [5]. Also, typical acquisition protocols of clinical images generally guide to a high intraslice resolution over an interslice resolution for attaining the stability of clearly visible image resolution with an appropriate signal to noise. A concise review on a conventional state-of-the-art previous methods for brain tumour localization can be categorized into fully automated and others need involvement of the user.

Voxel-based methods are extensively used for segmentation of the brain tumour. [6] performed an early trial on fuzzy c-means approach by using multi-sequence primary data. [7] performed segmentation of the tumour region, in which seed points are selected automatically using polished (FC) fuzzy connectedness algorithm. [8] used a fuzzy clustering with a knowledge based guidance technique followed by components which are 3D-connected to construct the shape of tumour. A semiautomatic method was performed to detect brain tumour in MR Images which used segmentation of growing seeded region and (NNC) neural network classification technique. But the method was a hybrid, semi-automatic and also segmentation process can be initiated only after pre-selecting the parts of tumour.

Generative models based methods are also applied for segmentation of tumour. Mixture Model (GMM) and an integrated Bayesian modeling classification are used to address a brain tumour multi-layered detection technique [9,10], [11]. This is also a Gaussian Mixture Model. There are some intrinsic limitations for the Voxel-based generative model: When insufficient Samples occur it is complex to build an explicit model, spatial information is not considered, data points are taken into account as independent samples which are derived from the population sample.

Machine learning (ML) have a greater influence in recent times on brain tumour segmentation: discriminative classifiers based methods have been widely emphasised for tumour segmentation. For example, [12] utilizes Support Vector Machines, [13] and [14] makes use of the Adaptive Boosting technique (AdaBoost)[15], [16] make use of the (RF) decision forest algorithm [17], and [18] adopts decision random forests models by unifying GMM and spatial context features. However, it lasts as a complex task to master a single, adequate classifier. For example, if we consider training a sample as each single pixel for classifier, then the training set will be too big to be applied directly with such amount of data. Therefore, sampling and training becomes a major problem, and it has greater impact on performance of classifier [19].

Supervised based machine learning algorithms utilize manually labeled (characterize) data for machine learning purpose. Decision random forests technique was used to categorize the regions of 3D MRI for localization of tumour. The superpixel based features for the detection of brain tumour in a framework of conditional random fields (CRF). This framework gives unsatisfactory results for low grade tumour regions. The approach proposed by [20] which mostly used the random forest based classification on the appearance and context-based features.

MR images based tumour's are characterized by texture and statistical properties of the tumour. Many existing approaches have explored the textural and first order intensity statistical features on a regional level [21]. Specifically, Soltaninejad and colleagues applied a high-dimensional feature set which includes sixteen statistical features, in order to capture the textural properties, 6 fractal features are used, 5 texture features and statistics of the region. But, feature set used in [21] included unnecessary features which has no or very little contribution to the overall performance. In this, we show improved performance by using subset of useful features incorporated with convenient processing steps in the learning pipeline [21].

A computerized hybrid technique presented for segmentation of brain lesion from MR images with the use of orthogonal (DWT) discrete wavelet transform, and (FCM) fuzzy c-means. This approach has been failed in the segmentation of brain tumour region from MR scan, when multiple modalities of brain images are used. A hybrid method which uses FCM clustering k-means for localization of brain tumour was proposed. [22] used incorporated approach by using region growing and threshold for localization of tumour regions. It's a hybrid technique which is dependent on comparative evaluation and restricted to specific tumour. The use of state of art superpixel based approaches over other segmentation algorithms (SLIC image segmentation [23]) to segment the multi-modal MR images, mitigating the issues in sampling and enhancing the sample characteristics. In spite of the fact that the

superpixel over the segmentation technique can be applied volumetrically in three dimensions[24], the use of segmentation in two-dimension is preferable, to represent the data sets with limited resolution in at least one dimension.

The multi-leveled Gabor filter bank is adapted to create the texture maps, due to this, the segmentation of the image in superpixel becomes easy, and level of accurate feature extraction becomes easy. Based on the extracted features, a different classifier is trained and do a brief analysis from the comparative analysis of the trained model. From the study of this comparative, we realise that tumour localization becomes more accurate. Finally, we incorporate that the due the creation of texton-map, the study of structural properties of brain and tumour region becomes easy. Our big-time investigations show that the proposed strategy deliberately outperforms both the original images and synthetic images.

In machine learning, the available benchmark data becomes essential to compare with other algorithms. In this type of research, this idea has been popular in recent days. The first ever bechmark was created for BraTS in 2012 and the event was also organized in the same year[2]. BraTS data contains images which are real and simulated. As different studies showed different accuracy as listed in the Table 1; so comparing the techniques and taking conclusions becomes difficult. Moreover, from the past studies, there is some space to improve the classification accuracy as the Dice and Jaccard value was not high enough. Therefore, we inspected texture based regional low-level statistical techniques which are not efficiently performed on MICCAI BraTS dataset before.

Proposed method

Our proposed framework for brain tumour localization is given in Fig. 2. For image denoising and enhancement, MR FLAIR images are preprocessed from the bilateral filter and texton-map images are generated. These texton-map images are segmented out into small regions, called superpixels [25]. From each superpixel, features of different types are extracted. After the extraction of features, different feature based classifiers are trained and built the learned model for a tumour, from the features and its corresponding ground truth labels of train set of superpixels. The parameters of classifiers are tuned and computed. For testing purpose, we used the same framework given in Fig. 2 except the class balancing is neglected. All these steps given in framework of Fig. 2 are explained in detail.

Preprocessing

In this stage, a series of initial preprocessing procedures are implemented before any special purpose processing. It enhances the image quality and also reduces noise. Brain images should be of less noise and maximum quality as they are more sensitive than other medical images. This stage consists of the following two sub-stages:

Table 1

Comparison of all the evaluating classifiers used to check the robustness of our purposed preprocessing method for Real HG, Real LG, Synthetic HG and on Synthetic LG images of the BRATS dataset by the parameter dice score.

Classifier Images	Support vector machine	Random forest	AdaBoostM1	RusBoost
Real HG images	0.78	0.88	0.86	0.87
Real LG images	0.73	0.81	0.83	0.81
Synthetic HG images	0.78	0.9	0.87	0.89
Synthetic LG images	0.76	0.83	0.85	0.83

Bilateral filtering

As given in Fig. 3, the idea of bilateral filter [26,27] is explored in order to combine grey level values based on geometric and photometric closeness preference of near values to distant values in both domain and the range. For more specification, consider (θ_x, θ_y) pixel centered location at a $(2N + 1) \times (2N + 1)$ of its neighborhood values.

$$\Psi_{\theta_x, \theta_y} = \{(\mu_x, \mu_y): (\mu_x, \mu_y) \in [\theta_x - N, \theta_x + N] \times [\theta_y - N, \theta_y + N]\}. \quad (1)$$

where $\Psi_{\theta_x, \theta_y}$ are neighborhood pixels values of (θ_x, θ_y) . The weighting factor of its spatial and radiometric values are given as

$$W_{\theta_x, \theta_y}^S(\mu_x, \mu_y) = \exp \left[-\frac{|(\mu_x, \mu_y), (\theta_x, \theta_y)|^2}{2\sigma_s^2} \right], \quad (2)$$

$$W_{\theta_x, \theta_y}^R(\mu_x, \mu_y) = \exp \left[-\frac{|(\mu_x, \mu_y), (\theta_x, \theta_y)|^2}{2\sigma_r^2} \right], \quad (3)$$

where $W_{\theta_x, \theta_y}^R(\mu_x, \mu_y)$ be values of intensity at its corresponding positions. The ensembling weights of the bilateral filter is product of 2 and 3:

$$W_{\theta_x, \theta_y}(\mu_x, \mu_y) = W_{\theta_x, \theta_y}^S(\mu_x, \mu_y), W_{\theta_x, \theta_y}^R(\mu_x, \mu_y). \quad (4)$$

In real time scenario, the value of pixels are weighted by its normalized filtered values.

$$\bar{I} \left(\theta_x, \theta_y \right) = \frac{\sum_{(\mu_x, \mu_y) \in \Psi} W_{\theta_x, \theta_y}(\mu_x, \mu_y)}{\sum_{(\mu_x, \mu_y) \in \Psi} W_{\theta_x, \theta_y}}. \quad (5)$$

Texton-map generations

We used a Gabor filter bank for the generation of texture maps of MR scans for a brain tumour. Among various filter bank bases, Gabor functions [28] supply the optimal solution in multiple domains (i.e. spatial and frequency). On that basis, Gabor filter bank is considered as the best to generate the texton-map in different ways.

1. Biological motivation: Visual cortex of mammalian brains have simple cells which are best modelled as family (self similar) by using 2D Gabor bank and k-means clustering.
2. Mathematical and empirical motivation: Due to the multi-orientation and resolution properties Gabor filter bank is best solution for spatial properties measurements. It provides the best tolerance space for recognition of pattern based tasks.

Texton-maps are small clustered regions of similar properties of image, generated by convolution of multi-dimensional and multi-orientation Gabor filter [28] defined in Eq. 6 is used: (i.e. The spatial domain of Gabor filter is basically modulated version sinusoidal wave of a Gaussian kernel function.)

$$G(a, b; \theta, \lambda, \psi, \gamma) = \exp \left(\frac{-a'^2 + \gamma^2 b'^2}{2\sigma^2} \right) \exp \left(i \left(2 \times \pi \frac{a'^2}{\lambda} + \psi \right) \right), \quad (6)$$

where filter size is declared by σ , wavelength of sinusoid is represented with symbol λ , ψ for shift phase and the γ is spatial measurement aspect ratio. Eq. 6, terminologies x_B and y_B are for the measurement of spatial orientation of the defined filter θ , as:

$$a' = a \cos \theta + b \sin \theta, \quad (7)$$

$$b' = a \sin \theta + b \cos \theta. \quad (8)$$

Due to the unsure tumour size, 5 scales of Gabor wavelets, each with 8 directions are used, as appeared in Fig. 4. MR FLAIR image is convolved with Gabor filter bank and its response vector with length of

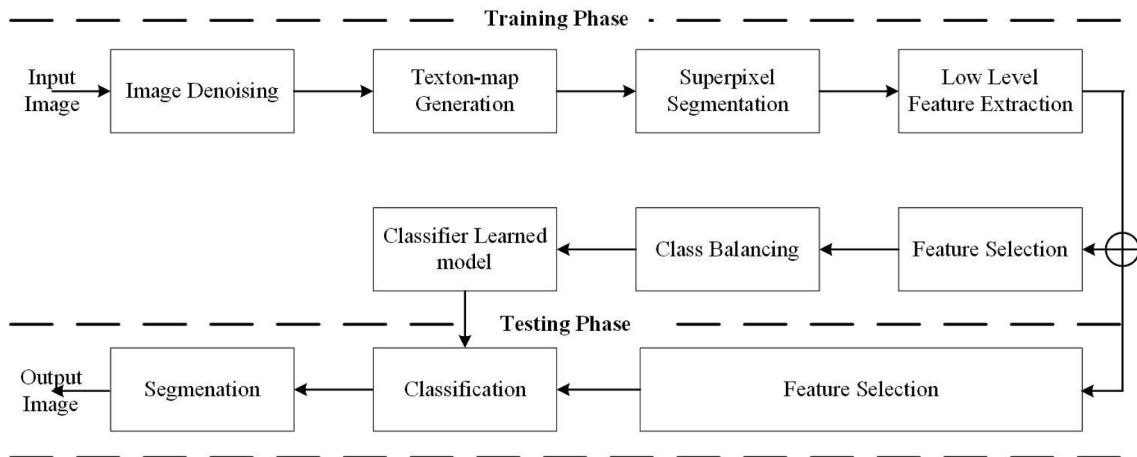


Fig. 2. The schematic block diagram of the proposed approach, that takes multiple FLAIR MR scans as an input for training and generates the learned model.

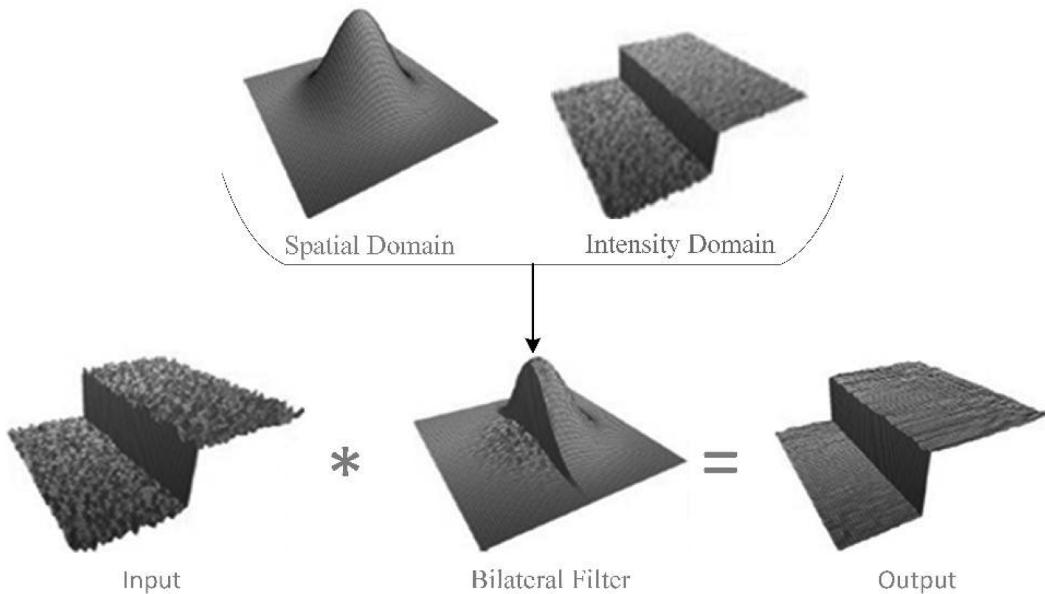


Fig. 3. Illustration of the bilateral filter used for deionising and image enhancement of MRI scans.

filter bank is generated and then clustered into k clusters by k-means clustering. The size of k is equal to number of filter orientations. The filter response vectors corresponding to each cluster are considered as the texton of a particular texture class. By assigning each pixel with a cluster number, an image of texton map is obtained. The extraction procedure of texton map is illustrated in Fig. 4. The texton features for each superpixel are then calculated using the histogram of texton map within each superpixel (See Fig. 5).

Superpixel segmentation

Different techniques and approaches in the field of medical imaging are used for superpixel extraction [5,29]. In actual, image pixels by default are not the representation of visual scenes. Specially, in MR imaging they represent the “artifact” of scanning process, just like in natural images [30]. Regions of superpixel are over segmented, pieces of images would be more natural and preferably in order to the lead for efficient processing. The superpixel distinguished properties are:

1. Computational efficiency: By the segmentation of images in small regions, the complexity to process the thousands of pixels by a few hundred superpixels.

2. Representational efficiency: Pairwise constraints between superpixels, while only for adjacent pixels on the pixel grid, can now model much longer-range interactions between superpixels.
3. Perceptually meaningful: Each superpixel is a perceptually reliable unit, for example all pixels in a superpixel are in all likelihood uniform in, state, shading and texture.
4. Completeness: In light of the fact that superpixels are aftereffects of an oversegmentation, most structures in the picture are rationed. There is next to no misfortune in moving from the pixel-grid to the superpixel map.

There are multiple existing approaches to obtain the superpixels [31,32,23]. We employ the simple linear iterative clustering [23] technique (SLIC) in order to aggregate nearby pixels into superpixels. In comparison with other superpixel approaches, SLIC is more memory efficient, fast, and gives excellent boundary adherence. It only acquires a single parameter for tuning, (i.e. desired number of superpixels) k . The detailed description of the SLIC is given in [23].

SLIC initialize the k initial cluster with cluster center C_k are sampled on a regular grid spaced by $S = \sqrt{\frac{N}{k}}$ pixels apart from the image with N pixels. The centers are first moved towards the lowest gradient position in a 3×3 neighborhood. Clustering is then applied. For each C_k , SLIC

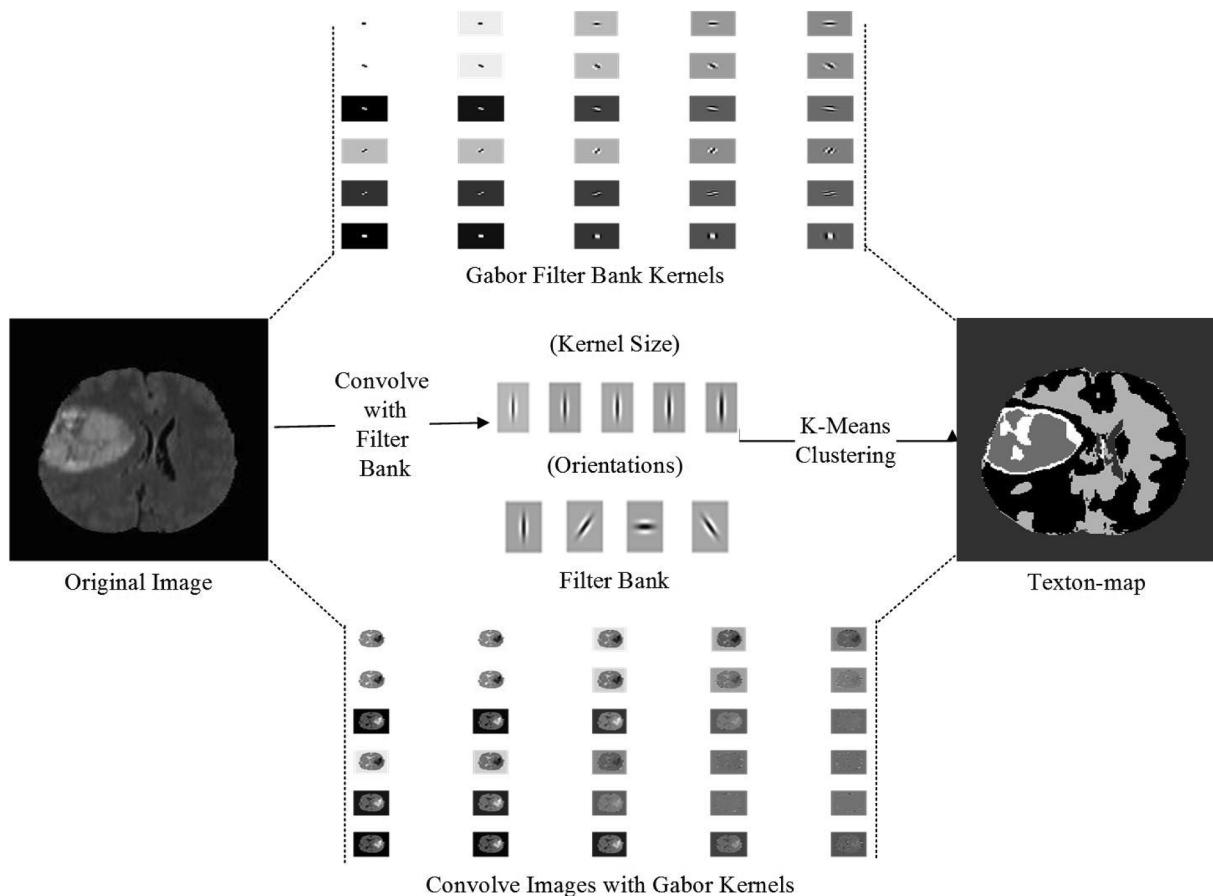


Fig. 4. The illustration of Gabor filter bank with its block diagram. The schematic visualization of Gabor kernel and orientations for texton-map generation.

iteratively searches for its best matching pixel from the $2S \times 2S$ neighborhood around C_k based on color and spatial proximity and then compute the new cluster center based on the found pixel. The iteration continues until the distance between the new centers and previous ones is small enough. Finally, a post processing is applied to enforce connectivity. In Fig. 6, we can see that the superpixels effectively represent correlative regions in the MR images without violating the tumor/edema boundaries.

Feature extraction

The proposed feature extraction includes eleven first order intensity statistical and five histogram level of texton-map features. Intensity features are shown Fig. 7. Intensity statistical features are low level features but we have made them significant in our approach by the extraction of features from the texton-map images. We used those feature techniques that illustrate the global properties of brain tissues [33] as shown in Fig. 7.

Feature selection

Selection of feature is an important step for machine learning and classification based task to decrease the time of computation, by removing the irrelevant and redundant features that may create the classification error. In our proposed work, we apply Minimum Redundancy Maximum Relevance (mRMR) approach for feature selection proposed by [34]. It is an efficient approach for the selection of most relevant features by removing the irrelevant features and select the most relevant ones. This selection is made on the basis of mutual information by identifying the similarities between the extracted features. For the features, f_i , maximum relevance between subset of

features S , is obtained by class c with the maximization of:

$$\max D(S, c) D = \frac{1}{|S|} \sum_{f_i \in S} I_M(f_i; c), \quad (9)$$

where I_M denotes the mutual information of feature f_i and the class c . The calculation of minimum redundancy is made by:

$$\min R(S) R = \frac{1}{|S|^2} \sum_{f_i, f_j \in S} I_M(f_i, f_j). \quad (10)$$

The proposed approach of feature selection is applied on entire vector of feature vector, leave one out cross validation is made by using the voting criteria. We employed the cross validation approach, in order to select the five best 5 features. In the proposed scenario, the selected features of one case are not necessarily similar for other cases. mRMR select randomly each time different features on the basis of mutual information. In each iteration, best performing features are selected.

Class balancing

In classification based problem, class imbalanced data is a common challenge, when distribution of one class is not uniform with other. Many machine learning techniques were unsuccessful to categorize skewed data [35]. We have majority of the data that has non-tumour region and very small portion is tumour region. Fig. 8 shows the resemblance of balance and the unbalance data. The technique used for balancing the data is Synthetic Minority Oversampling Technique (SMOTE) [36]. Fig. 8 first shows the actual count of samples for tumor and healthy region features and second is shows the synthetically created minority class samples.

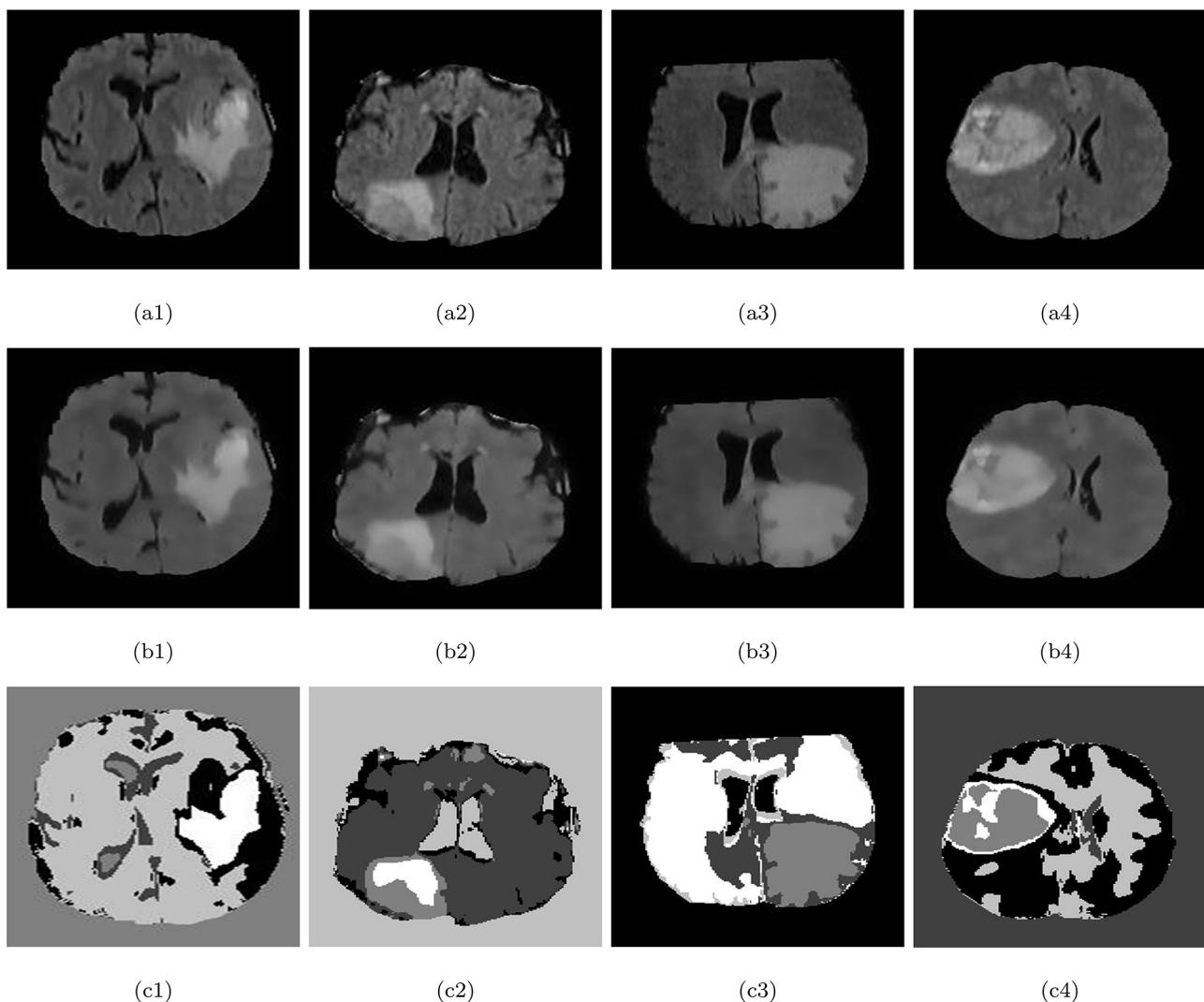


Fig. 5. The image (a1–a4) shows the original FLAIR MRI scans, image (b1–b4) shows the preprocessed and de-noised enhanced image from bilateral filter, image (c1–c4) the output of textron maps images.

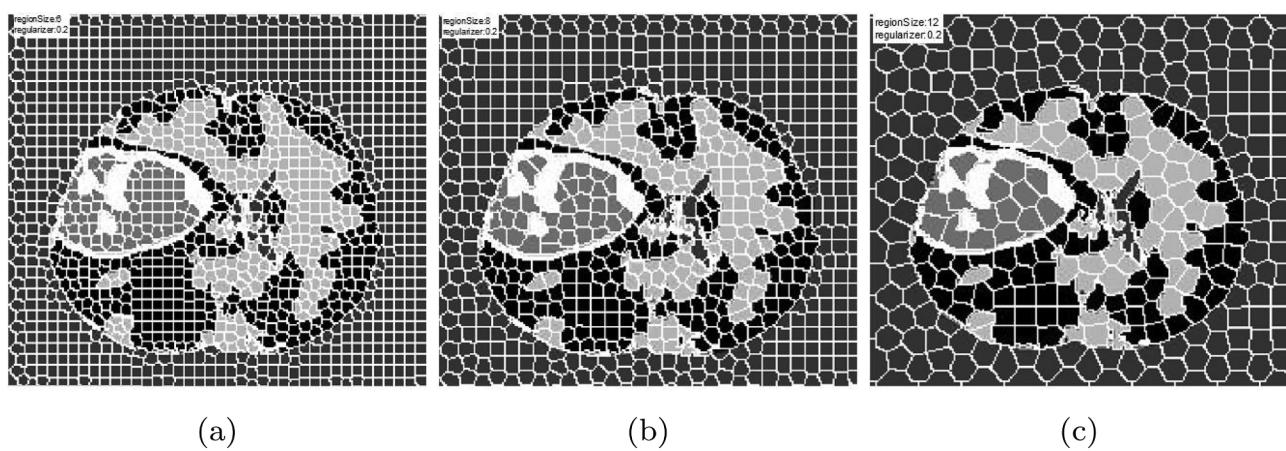


Fig. 6. Example of superpixel based image segmentation into small patches for variable region size windows: (a) superpixel segmentation with grid size region $R = 5$ (initial grid 5×5) and $r = 0.2$, (b) segmentation of superpixel with $R = 8$ (initial grid 8×8) and $r = 0.2$ and (c) segmentation of superpixel with $R = 12$ (initial grid 12×12) and $r = 0.2$.

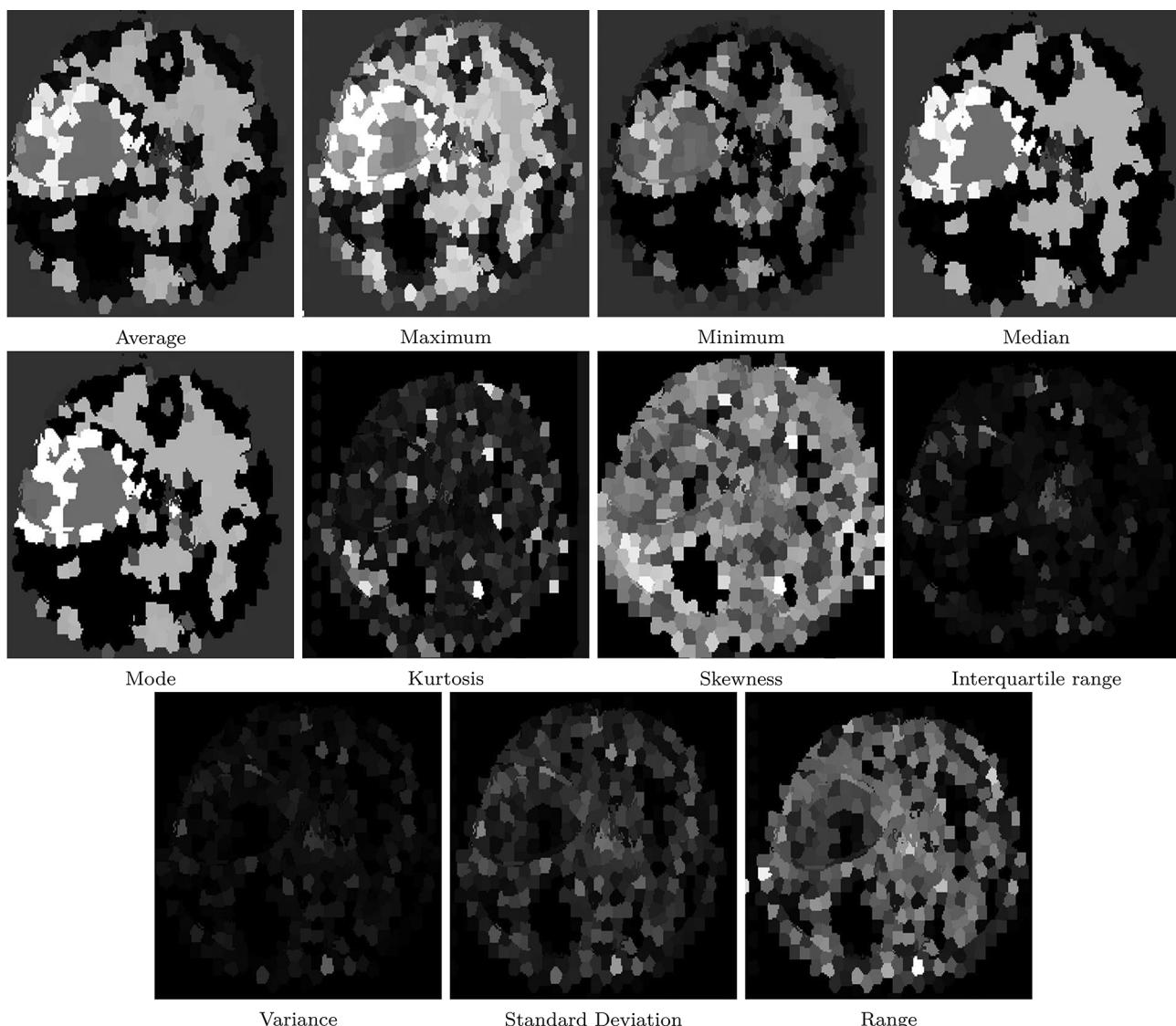


Fig. 7. Spatial representation of fist order intensity based statistical features. (a) Average Intensity feature, (b) Maximum intensity feature, (c) Minimum intensity feature, (d) Median intensity feature, (e) intensity feature.

Classification

Classification is basically supervised (ML) machine learning technique, where the training data is labeled that is used to learn a classifier and new data are classified using the training data. There exists many classifiers to classify data. Below are the few classifiers which we used in this work.

Support vector machine (SVM) is machine learning technique in which each feature is mapped onto ‘n’ dimensional space and classified into two different classes by using hyper-plane. SVM’s goal is to find the best dividing hyper-plane which maximizes the margin.

Random forest (RF) is an ensemble machine learning algorithm which uses large number of decision trees. This algorithm first takes some random data and then identifies set of key features to build each decision tree. RF provides internal error estimation and it is easy to parallelize [17]. RF is reasonably fast and also very easy to use. It handles sparse data well, and also overcomes the issue of over-fitting pretty well. RF has become very popular in short period of time because it can be applied to higher-ordered and non-linear datasets [37]. The parameter need to tune it is the tree size. Fig. 9(b) shows that the tree size of 20 is enough because after that line is straight. The version AdaBoostM1 is a boosting algorithm, which is used for binary

classification. This algorithm is best utilized on learners which are weak, that are incorporated to build a robust algorithm and preferably, occurrences are re-weighted than re-sampled (in bagging). Adaboost can be used to increase the performance of any machine learning algorithm.

Random under sampling (RusBoost) is a hybrid algorithm used to soothe the class imbalance problem. Machine learning techniques failed to successfully classify the skewed data, but RusBoost resolved the issue by integrating boosting and sampling techniques. We investigated all these classification techniques, and the outcomes are discussed in the section below. The tree size evaluation is shown in Fig. 9(a).

Experimental setup

In this section, the results are shown and compared with existing work on the BraTS data that contains separate low-grade (LG) and high-grade (HG) data. The results are in four sets (Synth-LG, Real-LG, Synth-HG, Real-HG). Quantitative evaluation was performed using three measures, and visualization results are also presented. These results are performed on HP-Spectre x360, quad-core i7-8705G processor, 16 GB RAM, 3.8 GHz using MATLAB 2014a. From Table 1, Random Forest technique out performed the other classifiers. So, Random Forest was used for the proposed method and the results are presented and

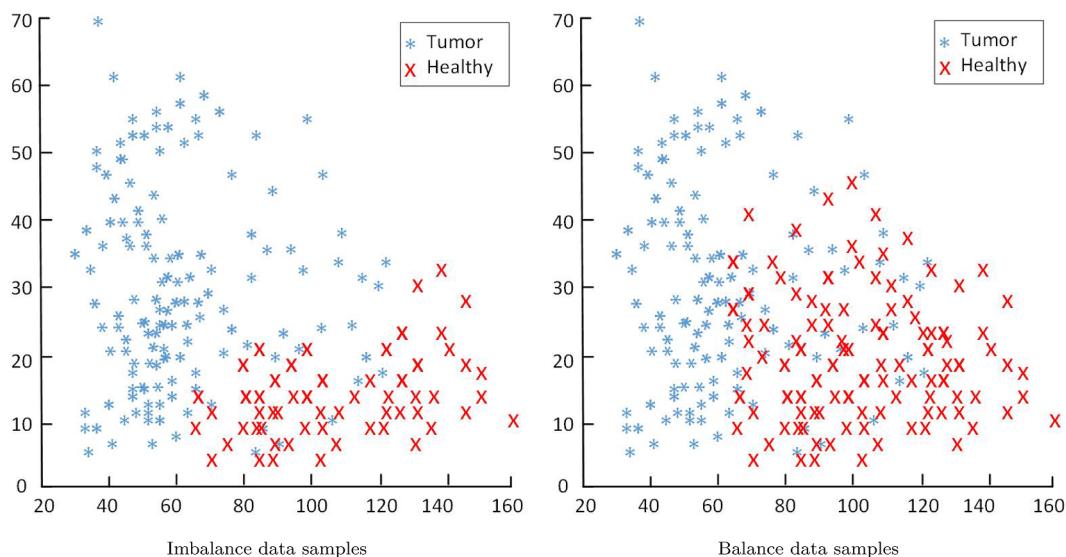


Fig. 8. Example of synthetically handling the problem of class balancing. Fig. (a) or Imbalance data example showing the majority and minority class samples and Fig. (b) or Balance data samples shows the induction of synthetically upsampling of minority class using SMOTE.

compared with the results of MICCAI BraTS challenge in Table 3. The detail results of proposed methodology for different classifiers are shown in Table 1.

Evaluation criteria

The comparison of the classifier's accuracy using methods based on superpixels is given in Table 1. The quantitative measuring parameter shows us how much the approach is efficient for hole brain tumour localization. For this, we extract the following components of (i.e. TP, TN, FP and FN) confusion matrix. For the understanding, these components are presented in Fig. 10. These components of confusion matrix are used for the calculation of evaluation measuring parameters (i.e. Accuracy, Precision, Sensitivity, Specificity). For the binary classification task (i.e., localization of tumour), four evaluation measures are used: accuracy (Acc), precision (Pre), sensitivity (Sen), specificity (Spe) and Dice-score (DS). The formulation of these measures are as:

$$Acc = \frac{Tp + Tn}{Tp + Tn + Fp + Fn} \quad (11)$$

$$Pre = \frac{Tp}{Tp + Fp} \quad (12)$$

$$Sen = \frac{Tp}{Tp + Fn} \quad (13)$$

$$Spe = \frac{Tn}{Tn + Fp} \quad (14)$$

$$DS = \frac{2Tp}{2Tp + Fp + Fn} \quad (15)$$

Table 2 shows the multiple evaluation measures performance for the best performing classifier i.e. Random forest in Table 1. It was observed that RF provides marginally better performance in classification when compared to AdaBoostM1, SVM and RusBoost with a comprehensive classification of dice score value for multiple classifiers correspondingly.

The Dice overlap ratio between the ground truth from manual annotation and the segmented tumour using multiple classifiers for the BRATS dataset is presented in Table 1. It can be seen that the overlap ratio using the RF based method is much better than that of other explored classifier for all the tumour grades.

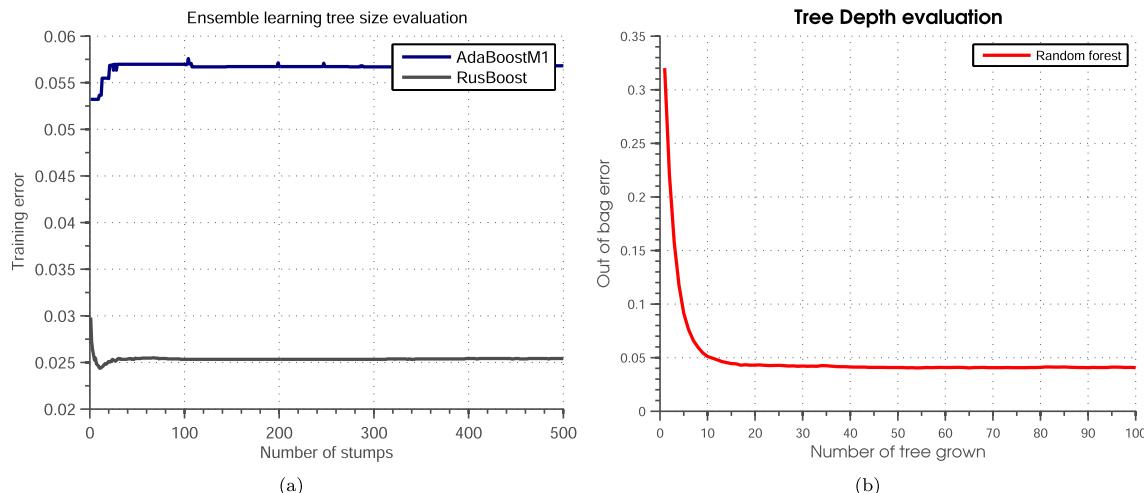


Fig. 9. Tree size evaluation during ensemble learning of classifiers, during training and OoBError. (a) represents the tree evaluation of ADaBoostM1 and RusBoost, (b) represents the OoBError during training of random forest.

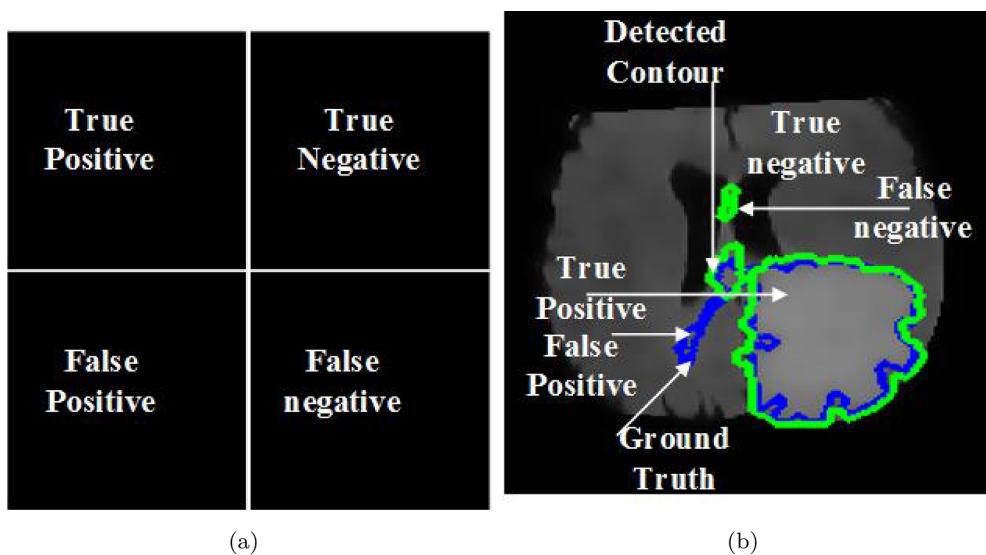


Fig. 10. This figure shows both confusion matrix components both in tabular and visually.

Table 2

Comparison of evaluation measures for the Random forest, upon on evaluation done by (leave-one-out cross-validation) for tumor localization in terms of Accuracy, sensitivity, specificity, precision and dice score separately for Real HG, Real LG, Synthetic HG and on Synthetic LG images of the BRATS dataset.

Performance Measure Images	Accuracy	Sensitivity	Specificity	Precision	Dice score
Real HG images	0.98	0.92	0.95	0.88	0.88
Real LG images	0.96	0.9	0.945	0.86	0.81
Synthetic HG images	0.98	0.92	0.96	0.86	0.9
Synthetic LG images	0.95	0.91	0.95	0.87	0.83

Figs. 12 and 11 show sample results of tumor localization for multiple classification methods smeared on the manual annotations for both small region tumor (Fig. 11) and low and high-grade tumour (Fig. 12). Different classifiers RF, SVM, AdaBoost and RusBoost methods are used to detect and segment different tumour types, but

Random Forest method provided better results when compared to other classifiers. Random Forest method can eliminate the false positive superpixels and (e.g. Fig. 12 also correctly classify the wrongly classified superpixels as tumour from AdaBoost, RusBoost and SVM which demonstrates high sensitivity of Random Forest. Comparison examples of segmentation for both high-grade and low-grade tumours in Fig. 11 and 12 illustrate that the segmented tumour boundary from RF is closer to the manual annotation compared to that of AdaBoost, RusBoost and SVM.

Visual results

In order to demonstrate the robustness of the proposed work, the tumour localization is visually shown in Fig. 12, that indicates the success of proposed approach for brain tumour localization from FLAIR MR scans.

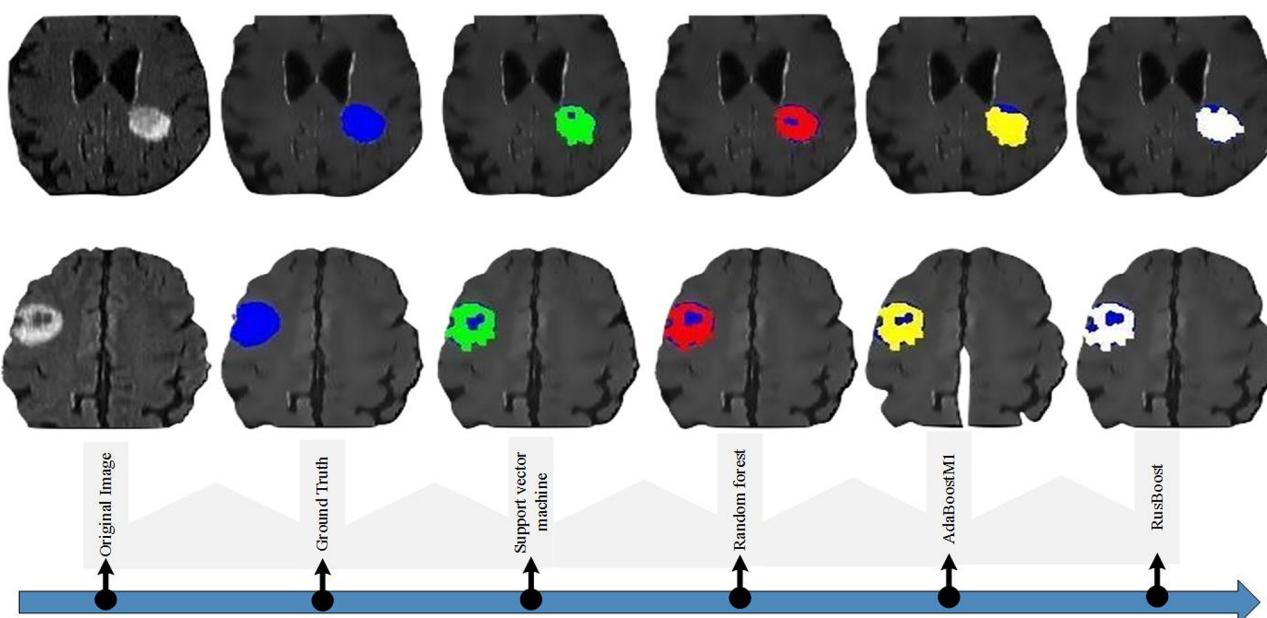


Fig. 11. Visual comparison of the tumor segmentation results of the classifiers on FLAIR images with HGG tumours. Case HG-10 and HG-12, the experts annotations and the results of SVM; RF; AdaBoost and RusBoost.

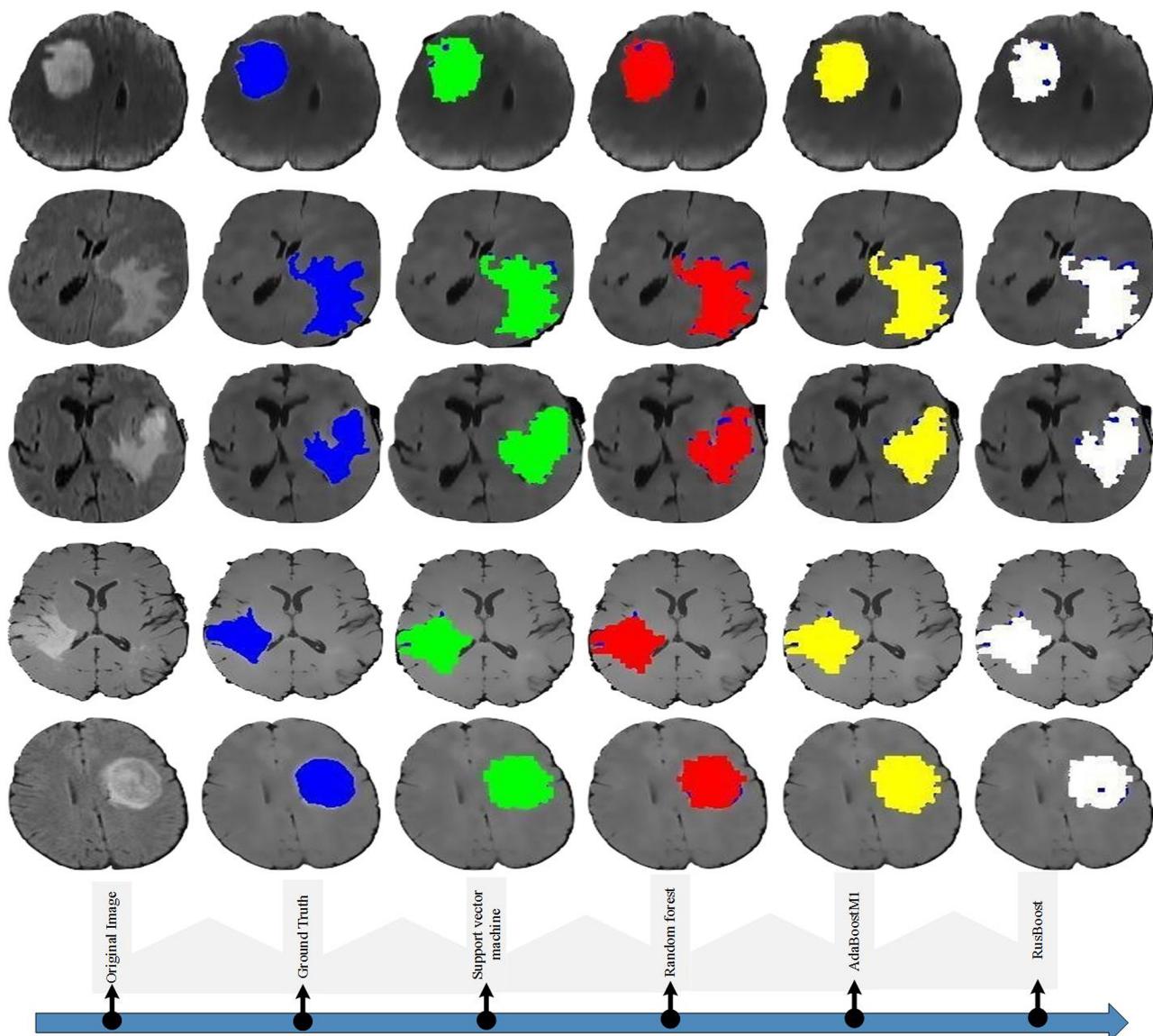


Fig. 12. Visual comparison of the tumor segmentation results of the different classifiers for multiple cases. For classifier SVM, RF, Adaboost and RusBoost results.

Failure modes

The limitations of the proposed approach are presented visually in Fig. 13, for these said of Brats-2012 the algorithm gives unsatisfactory results in some test images, and Dice score is also worse for those images

as compared to other images. The observation says that the explored features requires an improvement by introducing more robust features from former approaches. Definitely there is a research gap for future topic to overcome this problem, we have to explore more efficient features, that would help to improve the performance of the classifier.

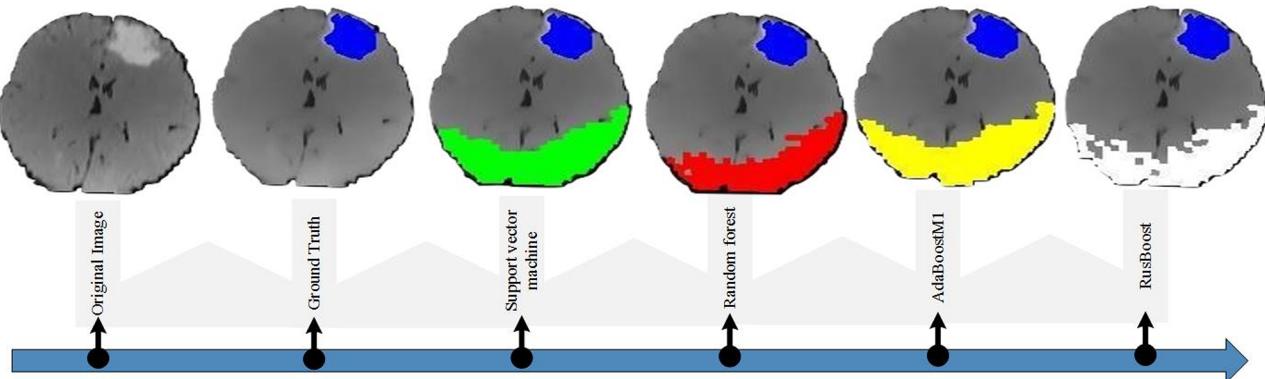


Fig. 13. In this figure some cases on which the classifiers are badly failed.

Table 3

Comparison of proposed method with the state-of-the-art in terms of Dice score separately for Real HG, Real LG, Synthetic HG and on Synthetic LG images of the BRATS (2012–13) dataset.

Sr. No.	Method	Complete (Real HG)	Complete (Real LG)	Complete (Real HG)	Complete (Real LG)	Time (min)
1	[38]	0.74	0.49	0.74	0.49	8 (CPU)
2	[39]	0.78	0.63	0.78	0.63	15 (CPU)
3	[40]	0.77	0.24	0.77	0.24	30 (CPU)
4	[41]	0.76	0.81	0.76	0.81	20 (CPU)
5	[42]	0.77	0.52	0.77	0.52	90 (CPU)
6	[43]	0.82	0.55	0.82	0.55	70 (CPU)
7	[44]	0.78	0.68	0.78	0.68	100 (CPU)
8	[45]	0.84	0.78	0.84	0.78	15(CPU)
9	Proposed method	0.88	0.81	0.88	0.81	2 (CPU)

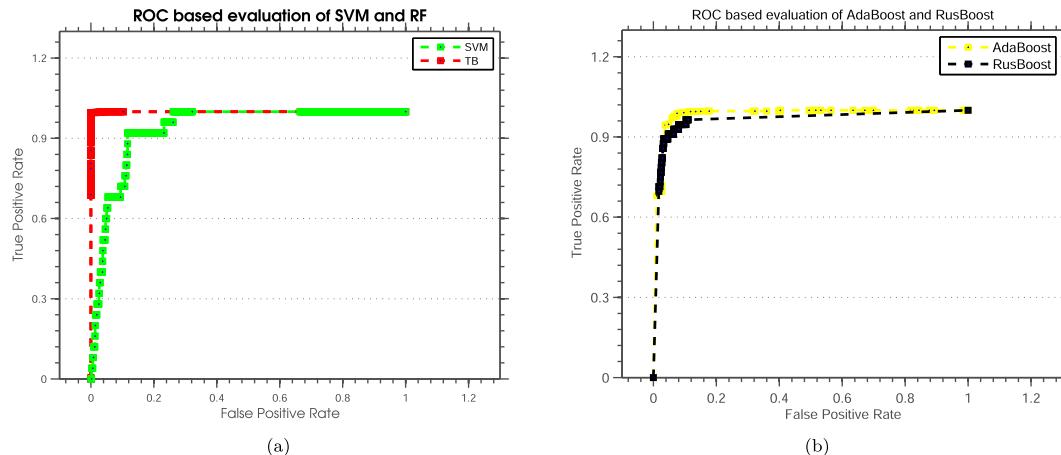


Fig. 14. Region of Curve (ROC) based, based evaluation for the used classifiers. (a) represents ROC evaluation of SVM and RF, (b) represents the ROC evaluation of AdaBoost and Random Forest.

Discussion

In clinical practice, FLAIR MR scans are usually acquired as a standard part of brain tumours localization. The experimental performance of our proposed approach is visually shown in Fig. 12 and quantitatively in Tables 1 and 2 demonstrate the performance of automatic localization approach for whole tumour region (edema and glioma) in FLAIR MR scans. The approach is also evaluated on synthetic images of BRATS 2012 dataset (FLAIR) with same pipeline of approach tuned for real image of BRATS dataset; the robustness of the approach is given in Tables 1 and 2.

The creation of texton-map and segmentation of images in small region called superpixel by choosing the superpixel of appropriate size that is critical to increase the accuracy of segmentation. Superpixels of appropriate size ensure that computation speed is fast and gives the information (i.e. sufficient) for efficient features extraction. However, superpixels of larger size may contain pixels of multiple classes which may lead to calculation of non-appropriate features (i.e areas of small calcification or haemorrhage), and also not appropriate for small size tumours. Definitely the superpixels of small size has higher probability of containing pixels of single class and performs well for lesions of small size. Some of the disadvantage of small size superpixels.

1. Create problem in computation of stable features.
2. Time of computation for small size regions is high.

The region size of superpixels, is obtained by the trained model classification accuracy. An optimization criteria for selection of region size will be explored in future, That can give a good commutation accuracy between its segmentation and computation time. The segmentation follows object edge boundaries majorly, specifically, when there is no clear and sharp edge information, it may go to defined region size.

In the proposed study, the region size is determined through visual inspection and depends on accuracy of trained classifier error rate.

The comparison of proposed approach on BRATS data with published work that uses the same dataset are given in [3] Table 3. The study proposed in this paper is for whole tumour localization (i.e. oedema and glioma) using FLAIR images. So, there may be some difficulty in comparison with available state of the art approaches on BRATS dataset.

However, the results of the proposed approach are in the comparable range with available state of the art methods and suggests an appropriate localization for whole tumour region. The current pipeline was able to localize tumour, only from FLAIR images. In future there is research gap to adopt the same approach to apply on contrast-enhanced T1C and T2 images for localization of high-grade glioma and edema separately and our focus to work in this direction. In this method, the importance of proposed preprocessing and texton-map generation, for image denoising and texture creation is appreciated by adopting the bilateral filter and Gabor filter bank. In the current study, we also note in Fig. 11 that small hypointense spots in the FLAIR (and corresponding T1w) may be calcifications, and the hypointense FLAIR region, which is excluded by the SVM method (Figs. 11 and 12) but included in the ensemble learning (RF, AdaBoost and Rusboost) analysis (Fig. 12), is haemorrhagic since there is hyperintensity in the T1c MR scans. The limitation of our proposed approach by using a single modality (FLAIR) analysis, that is not be possible to classify the different regions. Future studies will extend current approach for multimodal data. By using the multi-modalities, it will become easy to classify the different subtypes of brain tumours (i.e. necrosis, active tumour, infiltrative tumour, edema) by incorporating the information of multimodal MR scans. see Fig. 14.

Conclusion

Our proposed approach has gathered two recent and most useful trends for brain tumour localization: (1) creating the image in texture form by using the texton-map (2) extracting the features from the superpixels. In this paper, we adopted the three contributions. Firstly segmentation of superpixel is made on texton-map images, due to the texture appearance, it reduce computational cost of image segmentation in small regions, improves spatial smoothness of superpixels, and increases the accuracy of low level features. Second, we also introduced the concept of databalancing as shown in Fig. 8, that also helps in learning of vision based classifiers. Third, we developed a brief comparison of four different classifiers and analyse the performance in model training accuracy. Initially, our image denoising approach is shown to remove the false positive regions effectively. Our full system has been thoroughly evaluated on a challenging 30-subject of BRATS challenge dataset for both synthetic and real images and made comparison with the recent state of the art methods/approaches and shown the compare-able performance. The adaptation of describe pipeline of complete setup yields a comparable performance. The experimental results are shown that purposed pipeline gives the comparable performance with the state of the art method. In the future endeavors, we plan to explore alternative more robust features, classification and deep learning approaches. In last we conclude our work with this contribution that have made comparison with relegated method given in Table 3 are satisfactory and this intelligent system helps out in early diagnosis of brain lesions.

Acknowledgment

Bundle of thank for database organizers of BRATS-2012 for the evaluation of automated methods of brain tumour on MRI scans. This available database also providing manual ground truth label of tumor regions.

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