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BRAIN TUMOR DETECTION USING SUPPORT VECTOR MACHINES (SVMs)

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Abstract

Brain tumor detection is a critical task in medical imaging that requires accurate and reliable methods for early detection and treatment. In recent years, the use of Support Vector Machines (SVMs) has emerged as a promising approach for automated brain tumor detection. SVMs are a powerful machine learning algorithm that can be used for classification tasks, and they have several advantages over other machine learning algorithms such as neural networks and decision trees. This paper presents a review of recent research studies on brain tumor detection using SVMs. The review covers the advantages of using SVMs for brain tumor detection, the challenges associated with SVM parameter selection, and the reported accuracy rates achieved by different studies. The results show that SVMs have achieved high accuracy rates in the range of 90-95% in several studies. However, careful parameter selection is necessary to achieve optimal performance. Further research is needed to validate the performance of SVM-based brain tumor detection methods on larger datasets and to address the challenges associated with SVM parameter selection. In conclusion, SVM-based brain tumor detection is a promising approach that can help improve the accuracy and efficiency of brain tumor diagnosis.

Introduction

Brain tumor is a serious medical condition where an abnormal growth of cells occurs within the brain. It is a life-threatening disease that requires early detection and timely treatment. Brain tumors can be classified into two main types: malignant and benign. Malignant brain tumors are more dangerous as they tend to grow faster and it could escalate to other parts in the body as well as in the brain. Benign tumors, on the other hand, are usually slow-growing and will be moved to other body parts rarely.

Brain tumor detection is a critical task that requires accurate and reliable methods. Magnetic Resonance Imaging (MRI) is the most common technique used for the detection and diagnosis of brain tumors. However, manual interpretation of MRI images is a time-consuming and subjective process that can lead to errors and misdiagnosis. Therefore, automated methods for brain tumor detection have become increasingly important in recent years.

One such method is the use of Support Vector Machines (SVMs) for brain tumor detection. SVMs are a powerful ML algorithm, which could be utilized for regression-tasks & classification. They work by finding the best hyperplane that separates the data into different classes. SVMs have been successfully applied to a wide range of problems, including image classification, text classification, and bioinformatics.

In the context of brain tumor detection, SVMs can be used to classify MRI images into two categories: normal and abnormal. The SVM algorithm learns from a set of labeled MRI images and uses this knowledge to classify new, unseen images as either normal or abnormal. SVMs have several advantages over other machine learning algorithms, such as neural networks and decision trees. They are computationally efficient, have a low risk of overfitting, and are easy to interpret.

The use of SVMs for brain tumor detection has been extensively studied in recent years. Several research studies have reported high accuracy rates in the range of 90-95%. For example, a study conducted and reported an accuracy rate of 94.29% for brain tumor detection using SVMs. Similarly, a study conducted by Mohammad Tariqul Islam et al. (2020) reported an accuracy rate of 91.15%.

Despite these promising results, there are still some challenges associated with the use of SVMs for brain tumor detection. One of the main challenges is the selection of optimal hyperparameters, such as the kernel function and regularization parameter. The choice of these hyperparameters can

significantly affect the performance of the SVM algorithm. Therefore, careful tuning of these parameters is necessary to achieve optimal performance.
In conclusion, brain tumor detection using SVMs is a promising approach that can help improve the accuracy and efficiency of brain tumor diagnosis. SVMs have several advantages over other machine learning algorithms and have been shown to achieve high accuracy rates in several studies. However, further research is needed to address the challenges associated with SVM parameter selection and to validate the performance of SVM-based brain tumor detection methods on larger datasets.

Related work

Several researchers performed various studies on AD classification and their strategies. A comprehensive measurement for some of the studies have been depicted in this segment.
The work [1] presents a productive AD identification and an algorithm for the classification. Primarily, visual word bag technique has been used in order to enhance the texture attributes effectiveness such as GLCM, HOG, invariant feature scale transform as well as LBP. Further, clinical information besides imaging information have been highlighted by integrating attributes of texture with the attributes of clinical in order to produce the vectors of hybrid features. Moreover, features extracted from MRI segmented regions of the brain picture depicts white matter, CSF as well as grey-matter. Besides, this technique has been measured by utilizing the ADNI database. The simulation study assured that this technique surpassed the entire contemporary models when compared with few metrics like sensitivity, specificity as well as accuracy. The significant confine of this projected strategy has been that it was very intricate for detecting the projection of free space by utilizing this model. The extraction of features based on texture and projection of free space could give an effective discriminant capability.
The work [2] projected a novel learning technique based on SVM for classification of AD. In this projected SVM classification technique, features of spatial neighbors over anatomical fields have similar kinds of weights. Later, the lasso penalty cluster has been projected for sparsity of inducing structure, which assisted physicians in order to measure the significant areas incorporated in this AD. Moreover, in this study, the increased proximal-descent gradient technique has been proposed to solve the issue of learning. This simulation study has been conducted on a database online called ADNI. enhanced simulations have been carried out & the proposed technique effectiveness has been validated in terms of AUC, sensitivity, accuracy as well as specificity. This technique has been further used in the study as it is sensitive, where the factors impact the classification performance.
The work [3] proposed an effective model for the classification of AD that is an integration of novel selection of feature & ranking the feature based on t-test. This projected model incorporated 5 stages;morphometry model based on voxel utilized in order to compare global local variances related to gray-matter, and variances in volume of gray matter has been chosen to be VOIs (VOLUME-OF-INTEREST), VOIs to be as clusters of voxel, scores of t-test has been used to rank the features, by using SVM we can classify the features, and ultimately data fusion strategy used in order to augment the performance of classification. Further, the simulation outcome assured that the proposed model has been more productive when compared to contemporary models in metrics such as AUC, sensitivity, specificity as well as accuracy. Nevertheless, in a huge dataset, this technique is unsuccessful in attaining the effective classification outcome.
The work [4] proposed a classification system of multi-modality in order to exploit the data of multi-modal complementarity. Primarily, couple wise similarity has been utilized for defining the features modality such as biomarker measures of CSF, genetic data category, MRI regional volumes as well as intensities of signal based on voxel. Later, these multi-modality similarities have been integrated with graph fusion of non-linear techniques in producing classification of unified graphs. Simulation examination & validation assured that this strategy augmented the AD classification performance effectively. For instance, when samples of input have been less, then the classification model of multi-modality gets impacted & rate of classification lowers automatically.

The work [15] proposed an ITL (instance transfer-ensemble learning) model in order to classify the AD. primarily, this gravity transfer has been utilized in order to transmit the data related to source domain nearer to destination data. Later, effective variation among samples of destination domain & source transmitted domain samples has been researched through ITL utilization. Ultimately, transmitted samples of destination domain & optimum domain samples transmission have been integrated for the categorization. This technique is examined by utilizing a database called ADNI. Their simulation result assured that the projected technique has been surpassed when compared to contemporary approaches in metrics of mean as well as standard-deviation. AD classification through adjustment manually has been done in this study. The supervised technique has been utilized in present research study for overcoming earlier stated confines and to enhance the AD classification.

Methodology

The projected brain tumor detection system can be broken down into three main stages. In the first stage, an Anisotropic Filter (AF) is used as a filtering technique to remove noise from the brain MRI image. This is followed by an adjustment-based segmentation process that uses a structuring element in order to segment the image of the tumor that is filtered. The third stage involves applying morphological operations to identify the tumor's location. The flow of model has been depicted in Fig 1.

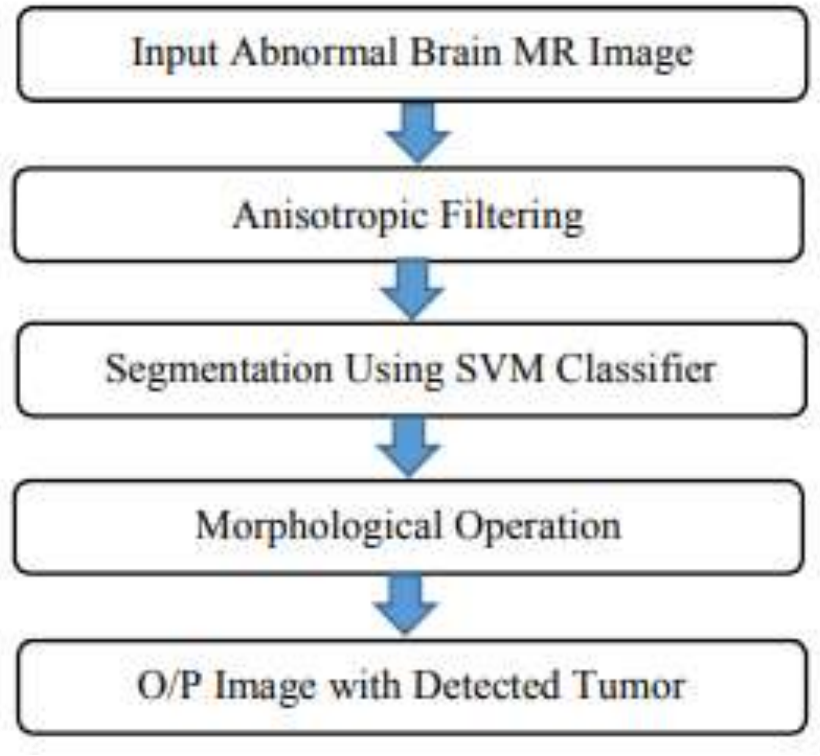

Fig. 1: Proposed approach flow chart.

A. Dataset

One of the abnormal images MR has been considered as input for tumor identification. The image of input has pixels of 256 x 256 and grayscale of 8-bit

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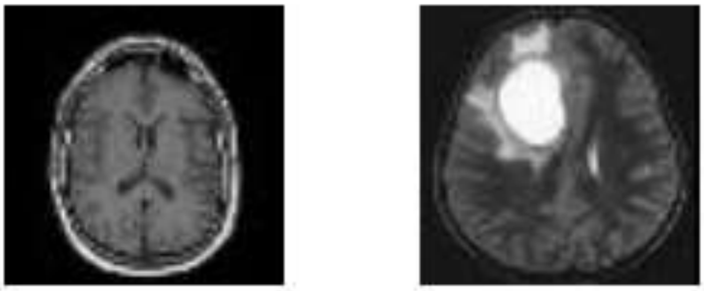

(a) Normal image (b) Abnormal image

Fig 2: MRI images of brain

B. Anisotropic-Filtering

The primary purpose of image filtering is to eliminate noise from digital images. Noise can significantly impact the quality of an image, and most image processing algorithms do not function optimally in a noisy environment. Therefore, image filtering is employed as a pre-processing tool. Anisotropic Filtering is one of the many methods used to eliminate noise in images and has been utilized in thesis for the purpose of denoising. Also, the general equation of anisotropic diffusion has been utilized for determining the procedure of image-diffusion.

$$\frac{\partial x}{\partial t} = div\ (c(m,n,t)\nabla I) = \nabla c \cdot \nabla x + c(m,n,t)\nabla x \ (1)$$

Where, ∇x Signifies gradient of an image &c(m, n, t) signifies coefficient of diffusion. Below representation depicts approximation of discretized by backward as well as in forward variances

$$I_{i,j}^{t+1} = I_{i,j}^{t} + dt \sum_{(k,l)\in N_4} g\left(I_{k,l}^{t} - I_{i,j}^{t}\right) \cdot \left(I_{k,l}^{t} - I_{i,j}^{t}\right) \qquad (2)$$

$$h\left(I_{k,l}^{t} - I_{i,j}^{t}\right) = \frac{c_{k,l}^{t} + c_{i,j}^{t}}{2} \qquad (3)$$

Where, N4 = {(i-1, j), (i+1, j), (i, j-1), (i, j+1)} signifies central pixel neighborhood $I_{i,j}^{t}$. We could notice that the pixel of noise is having robust action of diffusion & the pixel signal is having weak action of diffusion. Hence, noise could be eradicated & signals would be placed. There have been several approaches of diffusion for adopting fixed size of step for every iteration or entire image would be processed iteratively. In eq (4), the phase of iteration has been projected

$$dt = \frac{1}{4} c \qquad (4)$$

Here, ¼ has been utilized for promising the convergence in eq (2). Moreover, the ultimate output of the image has been attained through the procedure of iteration. In order to iterate the procedure, the IE (iteration error) has been utilized in order to control number of iteration & their formula has been:

$$IE = \frac{\|I^{n} - I^{n-1}\|}{\|I^{n}\|} \le T_{ie} \qquad (5)$$

The procedure of iteration will be stopped or paused when IE has been lower than or similar to Tie of tolerance.

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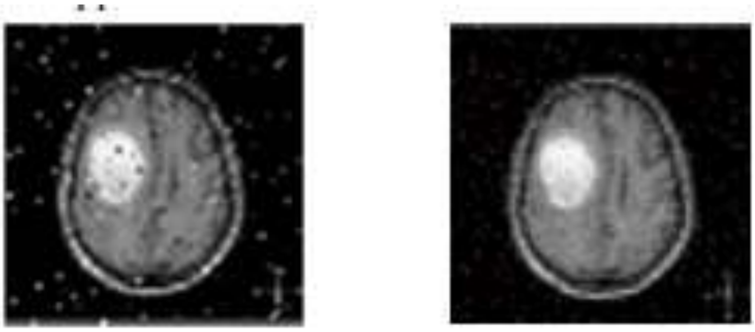

(a) Noisy Image with (b) AF output

Fig 3: I/O for AF

C. Segmentation of image using SVM

Image segmentation refers to the procedure of segmenting the picture into several parts in order to detect the objects & other associated data in images. SVM is a popular technique used for segmentation. In this approach, an optimal hyperplane is obtained for a given problem, such as the following simple problem:

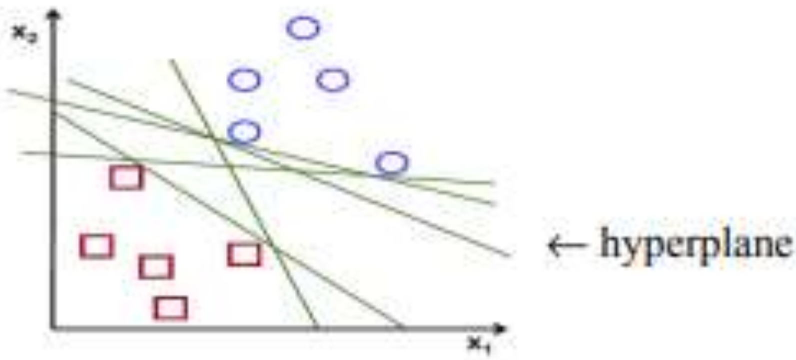

Fig 4: Hyperplane in SVM

Below equation represents equation related for determining hyperplane

$$p(x)= \propto_0+\propto^T\ z \qquad (6)$$

$$|\propto_0+\propto^T\ z| = 1 \qquad (7)$$

Here, z depicts the instances of training near a hyperplane. Usually, support-vectors have been considered as the nearest instances of training towards hyperplanes. We utilize geometry result, which provides the variance among hyperplane (∝,∝0) & point z

$$D = \frac{|\propto_0+\propto^T\ z|}{\|\propto\|}$$

Numerator has been similar to canonical plane & variance for support-vectors has been

$$D_{\ support\ vectors} = \frac{|\propto_0+\propto^T\ z|}{\|\propto\|} = \frac{1}{\|\propto\|}$$
-----(9)

Below equation, which has been 2 times the variance towards nearest instances depicts margin indicated to be M.

$$M = \frac{2}{\|\propto\|} \qquad (10)$$

Finally, M has been a maximizing issue, which is similar to minimal issue for R(∝) function subject for various restrictions. For categorizing correctly overall instances of training z the restrictions approach for hyperplane has been

$$\min_{\propto,\propto_0} R(\propto) = \frac{1}{2}\|\propto\|^2 \textit{subject to } y_i(\propto^T z_i + \propto_0) \geq 1 \ \forall_i, (11)$$

Where yi depicts every training instance's labels. This has been a Lagrangian issue optimization that could be solved utilizing lagrange multipliers for attaining ∝ weight-vector & ∝0 bias hyperplane

Experimental Study:

We have endeavored accurately on identifying the brain tumor in abnormal brain MRI images. For fulfilling the needed intention, removal of noise by utilizing anisotropic-filtering, and segmentation by utilizing morphological operations & SVM have been performed.

Performance analysis of AF

Speckle, salt & pepper and gaussian are 3 types of noises, which have been added as input image & then PSNR & MSE values were computed in the following way:

$$MSE = \frac{1}{pq}\sum_{i=0}^{p-1}\sum_{i=0}^{q-1} \| h(i,j) - g(i,j) \|^2 \qquad (12)$$

$$PSNR = 20 \log 10\left(\frac{MAX_f}{\sqrt{MSE}}\right) \qquad (13)$$

Where,
h presents original image matrix data
g depicts degraded image matrix data
p represents intensity values of row number for the image, where i represents row index.
q represents intensity values column number, where j represents column index.
MaxF has been considered as the maximal value of a signal, which is present in an image.

One such metric is the mean square error (MSE), which quantifies the difference between two images pixel by pixel. Another metric is the peak signal-to-noise ratio (PSNR), which measures the ratio between the maximum possible power of a signal and the power of corrupting noise. In this study, we apply these metrics to evaluate the performance of different filters on the input image with added Gaussian, Speckle, and Salt & Pepper noise. The filters are evaluated based on their ability to remove noise and improve the quality of the image. The input image is represented by the matrix data symbolized by 'h', while the degraded image is symbolized by 'g'. The variables 'p' and 'q' represent the row and column numbers of the intensity values of the images, respectively, & 'i' and 'j' represent their corresponding indices. The maximal signal value in the original image is denoted by 'MAXf'. The results of the evaluation are shown in the following table.

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Table 1: Measurement of PSNR as well as MSE over several filters

Model	Value of PSNR (dB)	Value of MSE	Type of Noise
Average Filter	73.12563	0.00334	Gaussian Noise (GN
	74.18460	0.00433	Speckle-Noise (SN)
	75.51239	0.00291	Salt & pepper (SP)
Median Filter	73.58866	0.00290	GN
	76.14531	0.00251	SN
	81.64881	0.00098	SP
Mean	72.88143	0.00511	GN
	72.83182	0.00501	SN
	74.70011	0.00377	SP
Wiener	73.54436	0.00421	GN
	73.51044	0.00410	SN
	72.50621	0.00475	SP
HPF (High-pass-filter)	69.56570	0.00711	GN
	66.51902	0.00617	SN
	67.25897	0.00628	SP
AF (Anisotropic filtering)	75.12785	0.00314	GN
	76.34125	0.00223	SN
	78.92458	0.00135	SP

Performance of AF has been exhibited in the below figures

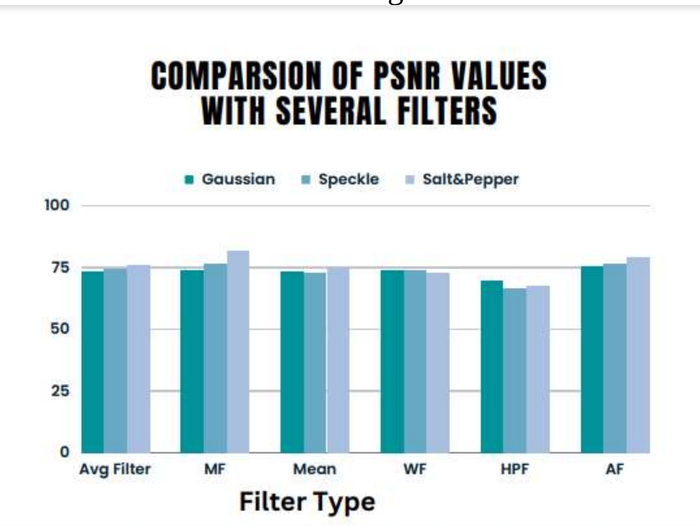

Fig 5:Comparison of PSNR values for diversified noises such as salt & pepper, gaussian & speckle

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In figure 5, we have compared PSNR values over diversified filters for distinct noises. The filters we have considered are as exhibited in the table. We have considered Gaussian, salt & pepper as well as speckle noises. The x-axis represents diversified filter types, whereas the y-axis represents PSNR values.

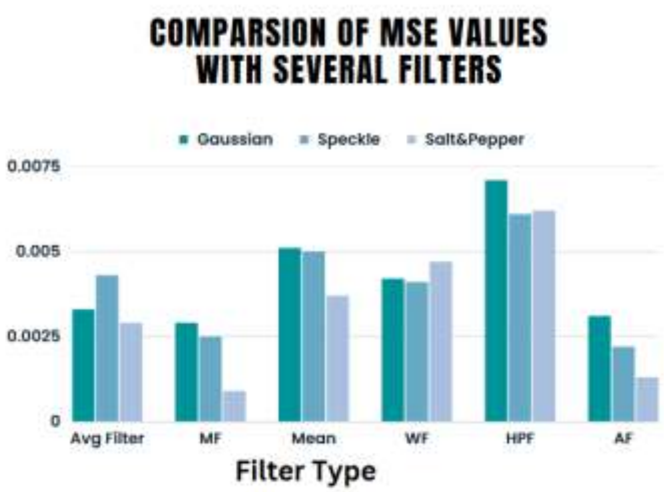


Fig. 6: Comparison of MSE value for pepper & salt, Gaussian as well as speckle noise among numerous filters.

The above graph presents a comparison of MSE values over diversified filters for distinct noises. The filters we have considered are as exhibited in the table. We have considered Gaussian, salt & pepper as well as speckle noises. The x-axis represents distinct filter types, whereas the y-axis represents MSE values.

After the removal of noise, the classifier SVM segments properly the image & then the operations in morphology have been performed. Besides, accuracy has been a measure for successful categorization. Accuracy has been provided by:

$$Accuracy = \frac{Number\ of\ correctly\ classified\ test\ samples}{Total\ samples} * 100\ \% \qquad (14)$$

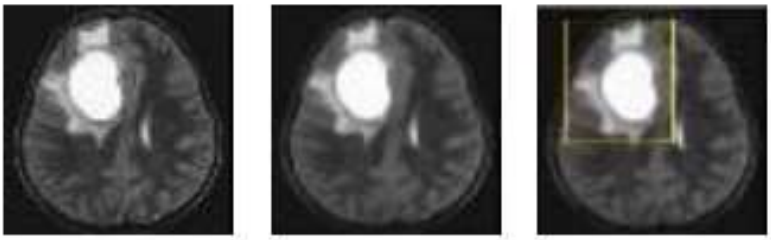
The purpose of segmentation considers pixels of number 380 and among them 320 have been classified accurately.

Hence, the accuracy would be calculated as

Accuracy =320/369*100

=86.7%

The below figure exhibits the ultimate outcome with every stage response.



(a) (b) (c)

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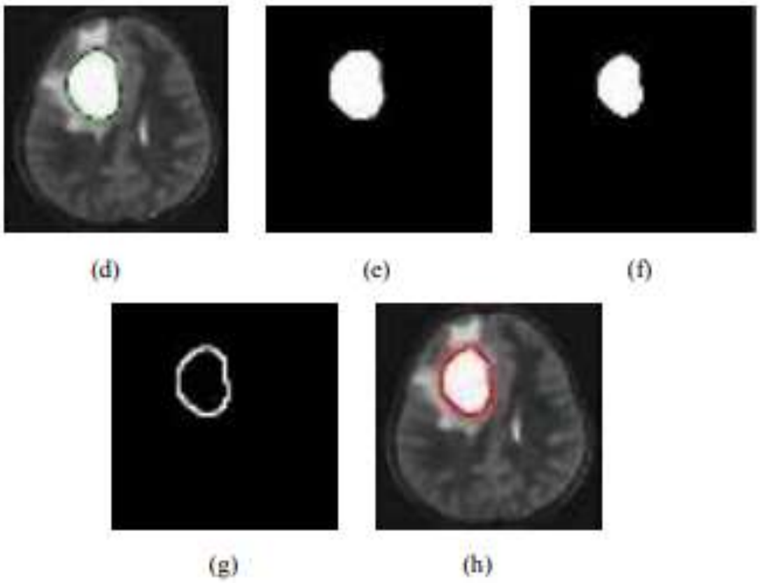

Fig 4.27: Numerous operations on MRI image of brain (1) image of input (2) image of filtered © Bounding Box locating (d) SVM (e) Tumor segmentation (f) image, which is eroded (g) Outline of tumor (h) Tumor detection

CONCLUSION

In order to accurately detect brain tumors in MRI images, it is necessary to remove noise from the input image. Anisotropic filtering was used for this purpose. Then, Support Vector Machine (SVM) was employed for segmentation, where the pixels were classified into two classes. Since the system was designed to work with any MRI brain image, an unsupervised learning kernel was chosen for SVM. Morphological operations were utilized for extracting the tumor from the area of segmentation. Finally, the approach was capable of detecting the tumor in an accurate way.

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