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IMAGE & SIGNAL PROCESSING

An Enhancement of Deep Learning Algorithm for Brain Tumor Segmentation Using Kernel Based CNN with M-SVM

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Abstract

The brain tumor can be created by uncontrollable increase of abnormal cells in tissue of brain and it has two kinds of tumors: one is benign and another one is malignant tumor. The benign brain tumor does not affect the adjacent normal and healthy tissue but the malignant tumor can affect the neighboring tissues of brain that can lead to the death of person. An early detection of brain tumor can be required to protect the survival of patients. Usually, the brain tumor is detected using MRI scanning method. However, the radiologists are not providing the effective tumor segmentation in MRI image due to the irregular shape of tumors and position of tumor in the brain. Accurate brain tumor segmentation is needed to locate the tumor and it is used to give the correct treatment for a patient and it provides the key to the doctor who must execute the surgery for patient. In this paper, a novel deep learning algorithm (kernel based CNN) with M-SVM is presented to segment the tumor automatically and efficiently. This presented work contains several steps that are preprocessing, feature extraction, image classification and tumor segmentation of brain. The MRI image is smoothed and enhanced by Laplacian of Gaussian filtering method (LoG) with Contrast Limited Adaptive Histrogram Equalization (CLAHE) and feature can be extracted from it based on tumor shape position, shape and surface features in brain. Consequently, the image classification is done using M-SVM depending on the selected features. From MRI image, the tumor is segmented with help of kernel based CNN method.. Experimental results of proposed method can show that this presented technique can executes brain tumor segmentation accurately reaching almost 84% in evaluation with existing algorithms.

Keywords Brain tumor segmentation · Deep learning algorithm · Kernel based CNN · M-SVM · Image classification

Introduction

An abnormal group of cells can be formed by uncontrollable cells division around or inside the brain of human. This kind of group cells can affect the usual functions of brain and healthy cells of brain can also be affected by this. This brain tumor disease can direct to disability of person and deadly is occurred when there are severe conditions. In general, the brain tumor has two types: one is benign and another one is malignant tumor. The benign tumor cannot spread out in a sudden method and the adjacent healthy tissues of brain are also not affected by this kind of brain tumor, but the malignant brain tumor is one type of cancer tumor that can direct to patient's death and it will expanded with worst condition and also affect the neighboring healthy brain tissues. As a result, the Magnetic Resonance Imaging (MRI) scanning method has been presented to identify the tumor in brain of human at early stage to avoid the number of death. The MRI system can be very special one way to find the brain tumor and it is good cancer screening process compared to computerized tomography (CT). The useful information about size, shape, metabolism and position of brain tumor has been noticed by using MRI for diagnosis process. Usually, the MRI method can give methods to make sure the tissue contrast by utilizing the work of normalization that generates it an extremely flexible machine for imaging characteristic structures of awareness in human brain such as normal and malignant tumors [1–5].

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In medical side, the difficulty of brain's cells division and their nuclei from content of MRI image can be faced by the radiologists. At present, the segmentation of brain tumors from MRI image can be a challenging difficulty due to structure and location of tumors in human brain when using a multi-modal imaging data. Thus, the image segmentation can be the essential complexity in tumor detection in brain MRI image. But the tumor segmentation of separation process is very important to identify the brain tumor and efficient diagnosis. Quantitative and qualitative data about the benign tumor or cancer tumor can be given by the proper segmentation process and it can be utilized to recognize what are the good treatments for patient and to get the better plan by doctor who treats the patient. Effective tumor detection can be happened when image analysis is going to be easy to understanding and segmenting. Hence, numerous algorithms and methods have been presented for manual, semi and fully automated tumor segmentation due the complicated tumor segmentation process in MRI image. Many of them were executed on small datasets only [6–10]. Therefore, now days, deep learning based methods and algorithms are introduced to give the better results in tumor segmentation for tumor recognition in brain. Already, the Deep Convolutional Neural Networks (DCNNs) was employed to overcome the issues of tumor segmentation and major performance enhancement has been provided by this algorithm compared to the previous algorithms or methods. In this paper, the automated algorithm kernel based CNN with M-SVM is introduced to effective brain tumor segmentation with low time complexity, low error rate and high accuracy.

Related works

Architecture of deep learning algorithm CNN for brain tumor segmentation has been proposed in [11]. In this algorithm, both global and local features were incorporated as framework is significant while it comes to progression of brain tumor segmentation in brain image. A new nucleus segmentation framework was presented in [12] by employing the DCNN and selection-based sparse shape method. This method was started with a deep learning-based iterative region merging method to start the curves, and afterward robust top-down shape inference and competent bottom-up shape deformation has been used alternatively to attain exact nucleus segmentation in brain. An effective method was introduced in [13] which combined the discrete wavelet transform (DWT) and Deep Neural Network (DNN) to categorize the brain MRI image into Normal and three kinds of malignant brain tumors such as metastatic, sarcoma and glioblastoma. An easy and consistent brain tumor segmentation method has been presented in [14] for MRI images throughout recursively and intensely conveying a learnt random forest-based knowledge to direct the SVM classifier in the brain tumor segmentation task. A survey of the state-of-the-art algorithms was given in [15] depending on the conventional and deep learning methods for tumor segmentation. The existing deep learning architectures were reviewed in [16] that are exploited for anatomical brain lesions and brain structure segmentation, afterward the, speed, implementation and assets of deep learning methods have been discussed and summarized. A novel multi-fractal (MultiFD) feature extraction and supervised classifiers were proposed in [17] for enhanced brain tumor segmentation and identification and modified AdaBoost algorithm is also presented to consider the extensive unpredictability in features of surface diagonally hundreds of multiple patient MRI slices for expanded tumor and non-tumor tissue categorization. An automatic segmentation technique was presented in [18] depending on the CNN, investigating a small 3×3 kernels. A feature recombination has been presented in [19] throughout linear extension and density to produce more compound features for semantic segmentation of brain tumor in image. A segmentation SE (SegSE) block has also been presented for feature recalibration that gathers related information, whereas retaining the spatial meaning. Automatic brain tumor segmentation was presented for brain images to the accurate segmentation of brain tumor in MRI image. This kind of technique has been employed for tumor segmentation as a categorization difficulty. Moreover, the local independent projection-based classification (LIPC) method has been exploited to categorize every voxel into various classes [20].

Proposed methodology

In this paper, four steps are suggested to segment the brain tumor from MRI image for early detection of brain tumor. The overall process of our presented automatic tumor segmentation method has been established in Fig. 1. Initially, given sample MRI image can be preprocessed using combination of laplacian of Gaussian filtering method and CLAHE method. Here, the GoS method is applied to remove the noises and unwanted background parts from MRI image and then the image contrast can be enhanced with help of CLAHE to give the enhancement of image for further process of feature extraction, image classification and tumor segmentation. After that, the feature is extracted from the enhanced image using SGLDM method depending on the spatial distribution of gray levels of region of interest (RoI) in terms of shape, structure and place of tumor in image. The feature is selected from the extracted features based on the tumor features. Then, the selected feature can be given to the M-SVM classifier to classify the given image as normal or abnormal. If MRI image is abnormal, then a deep learning algorithm kernel based CNN is applied to segment the tumor in image. Finally, the tumor is classified into benign or malignant tumor. Hence based on

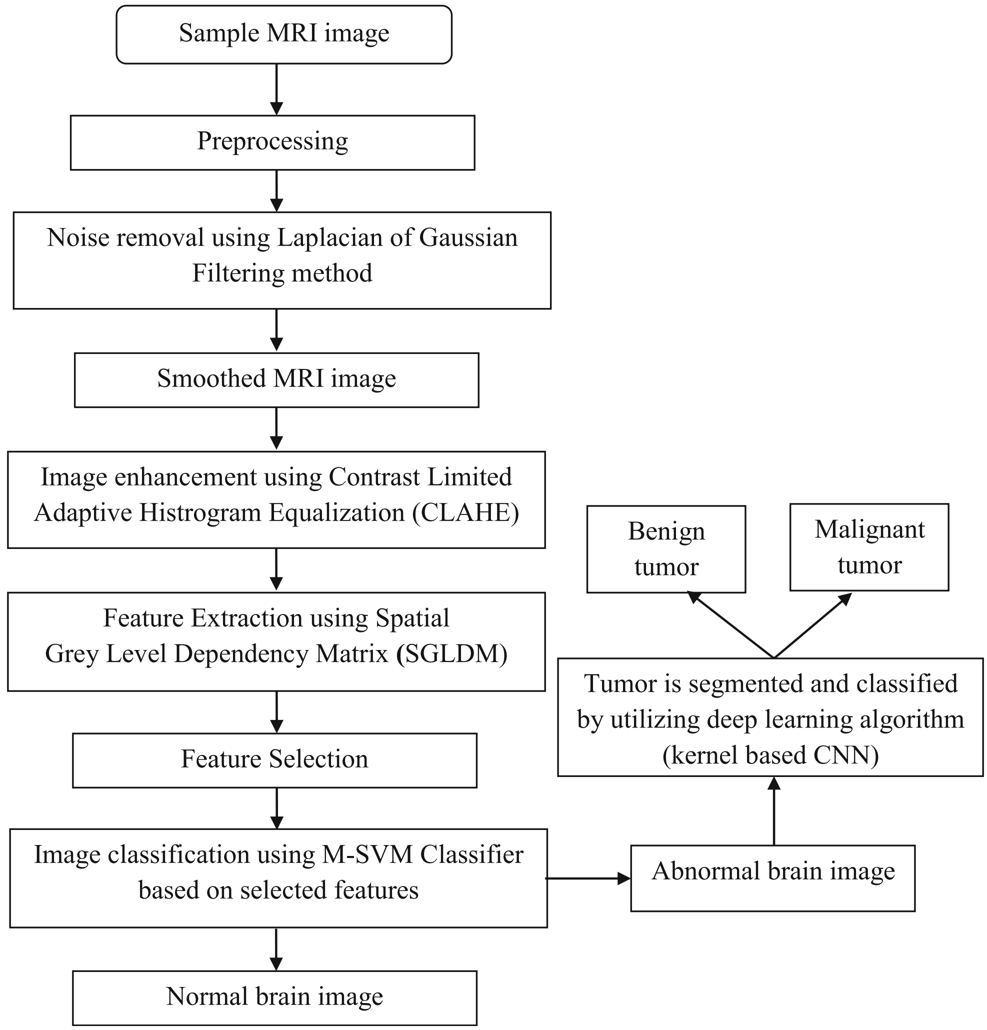

Fig. 1 Overall Process of Proposed Methodology

tumor treatment is started by doctor who care the patient. It will help to give the suggestions to doctor for surgery of tumor in brain and it can save the patient life immediately.

This proposed methodology contain following steps to accurate brain tumor segmentation:

- Preprocessing using combination of LoG and CLAHE
- Feature Extraction using SGLDM
- Image Classification using M-SVM classifier
- Tumor segmentation using deep learning algorithm

Preprocessing using combined LoG and CLAHE

In this preprocessing step, the noises and unnecessary backgrounds of MRI image is eliminated using Laplacian of Gaussian filtering method and then the image is smoothed. This smoothed image is enhanced with help of CLAHE method to give the brightness differentiation between object and background image that will be helpful to additional process of brain tumor segmentation. In this method, the second derivatives of MRI image can be estimated by laplacian filtering method that is applied to evaluate the rate at modifications of first derivatives of captured image. While changes are happened in adjacent pixel values are continuous or edge sequence, this is used to describe the edges of image and information of edge recognition. In general, the laplacian filter's kernals having negative values in the manner of cross pattern that can be centered within an array process. In this array, the corners contain zero or positive value and centre value of array may be positive or negative value. The example of possible kernel is in the form of

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & -2 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

The above array has negative central peak, so it is known as negative laplacian. The signs of elements of array are reversed by using -1 s and a + 2 to obtain a positive laplacian.

The areas of edges in MRI images can be discovered by using the derivative filters of laplacian filters. The Gaussian filter is applied in MRI image before using the laplacian filter to smooth the given MRI. This type of two step processes is known as operation of Laplacian of Gaussian filter and it is calculated by following Eq. (1).

$$P(p,q) = \nabla^2 f(p,q) = \frac{\partial^2 f(p,q)}{\partial p^2} + \frac{\partial^2 f(p,q)}{\partial q^2} \tag{1}$$

This kind of lapalacian of Gaussian filters' functions are used to smooth the MRI image by reducing the noises and it is calculated by using the following Eq. (2)

$$LoG(p,q) = -\frac{1}{\pi\partial^4}\left[1 - \frac{p+q^2}{2\partial^2}\right] e^{-\frac{p^2+q^2}{2\partial^2}} \tag{2}$$

Hence the image is smoothed and converted into gray level image. After that, the contrast enhancement of MRI image is done using CLAHE technique to provide the brightness differentiation of brain and background of MRI image. It is a special method of histogram equalization technique and MRI image is enhanced adaptively by functions of CLAHE method and it is also be utilized to enhance the MRI image's intensity contrast. In the given MRI image, CLAHE can works on little regions, known as shape of brain, rather than the whole MRI image. Every contrast of image has been developed. As a result, the definite histogram is matched by output region of histogram approximately using parameter of distribution. The parts of neighboring in image have been after that united exploiting bilinear interpolation to remove unusually influences the boundaries. Finally, the MRI image is enhanced to further process to tumor segmentation.

Feature extraction using SGLDM

After the preprocessing, we extract the features from the MRI image using SGLDM method for image classification accuracy. The better suggestion is given this process for M-SVM classifier to classify the image and dimensionality can also be reduced for easy to workout the image classification. Before MRI image classification, we execute the feature extraction using the method SGLDM. The features are based on structure, shape, surface of tumor in MRI image.

In this kind of feature extraction, a function of co-occurrence matrix is obtained to extract the features from the preprocessed MRI image. By applying SGLDM method, the second order statistical texture features are extracted. From the given sample MRI image, the statistical data is extracted by co-occurrence matrix according to the pixels pairs' sharing. By using angle θ and distance d, pixels pairs in MRI image can be estimated. The distance d can separate the pixel pairs during the process. Depending on the gray level values of given MRI image, the pixels' pairs are counted for extraction of features. The co-occurrence matrices can be executed to four various distances d in the directions of vertical, horizontal and two diagonal. Angle θ may be in the values of 0°, 45°, 90° and 135°. The distance d and angle θ can be described to estimate the co-occurrence matrix.

In this paper, six features are used for MRI image such as Contrast, mean, variance, Entropy, energy and homogeneity. The equations of these six features are given as

$$contrast = \sum_a \sum_b (a-b)^2 f(a,b) \tag{3}$$

$$mean = \sum_a \sum_b f(a,b) \tag{4}$$

$$variance = \sum_a \sum_b (1-mean)^2 f(a,b) \tag{5}$$

$$entropy = \sum_a \sum_b f(a,b) log(f(a,b)) \tag{6}$$

$$energy = \sum_a \sum_b f((a-b))^2 \tag{7}$$

$$homogenity = \sum_{a,b} \frac{1}{1+(a-b)^2} f(a,b) \tag{8}$$

From the Eqs. (3-8), $f(a, b)$ represents the co-occurrence matrix's elements that can be the likelihood of moving from a pixel with gray level values a to b.

Using above algorithm the features have been extracted from MRI image, and then features are selected from the extracted features based on tumor structure to classification of MRI image.

Image classification using M-SVM

In this process of classification, the selected features are given to the M-SVM (Multiclass-SVM) classifier to classify the MRI image as normal or abnormal. In general, the SVM can be a binary classifier and it is also being exploited for the two class classification difficulties. For the multi-class classification, SVM cannot be utilized directly due to different difficulties. Slightly in these kinds of difficulties of classification it is enhanced to employ the combination of different binary SVM classifiers that is called as multi-class SVM classifier. In this supervised learning method, a set of hyperplanes can be utilized to divide six classes of data in MRI image. Support vectors can be act as input data elements that can describe boundaries and the decision boundaries have been discovered from training data for MRI image. The SVMs can give faster work and more deterministic than the traditional neural networks. It is depending on the decision planes beginning. A decision plane can divides between a set of items containing various memberships of class. The SVM utilization contains two fundamental steps: training and testing of image.

Conventional multiclass classifiers cannot to solve the multiclass difficulties efficiently. Thus, in this paper, multiclass SVMs are used to classify the MRI image. Here, a two-class classifier can be designed depending on the feature vector ϕ ($\overline{a}$, b) and this feature vector has been derived from the pair containing input features of brain image. In this classification, the classifier can select the class during the testing time and it calculated as follows

$$b = argmax_{b'} \overline{w}^T \phi\left(\overline{a}, b\right) \tag{9}$$

During the training process, the margin can be formed as gap between this value for the accurate class and for the adjacent additional class. Therefore, the quadratic program formulation is given as.

$$\forall_i \forall_b \neq b_i \overline{w}^T \phi\left(\overline{a}_i, b_i\right) - \overline{w}^T \phi\left(\overline{a}_i, b_i\right) \geq 1 - \xi_i \tag{10}$$

This kind of common method has been enhanced to provide a multiclass formulation of different linear classifiers. Hence, the MRI image can be classified by the M-SVM classifier as normal image or abnormal image depending on the selected features of tumor. If MRI image is abnormal, then it indicates that the brain has tumor.

Image segmentation using deep learning method

If M_SVM classifier classified the MRI image as abnormal image, then the deep learning method CNN is applied to segment the tumor from the brain MRI image efficiently based on the kernels with less error rate and less time. In this process, CNN is combined with M-SVM classifier. The kernel based CNN can be utilized to segment the tumor and M-SVM classifier is used to tumor classification as benign or malignant. CNN can be a multilayer neural network with a general formation. At present, the popular RBF (Radial Basis Function) kernel has been utilized as intelligent selection of the fundamental kernel. In this paper, spectrum mixing is added to the basic kernel to augment flexibility for the tumor segmentation process: the kernel based CNN is calculated using the following Eq. (11)

$$K_{CNN} = \sum_{i=1}^{I} a_i \exp\left(1 - \frac{1}{2}\left\|\sum_i^{1/2}\left(q - q'\right)\right\|^2\right) \cos\left(q - q', 2\pi\mu_i\right) \tag{11}$$

The architecture of kernel based CNN has shown in Fig. 2. In this work, the neural networks is trained at two various steps to assist two levels of convey the deep learning process for tumor segmentation in MRI image. First step is employed for the convolution layer of CNN and second step for the completely related layer. In the initial transmission learning level, the CNN's convolution weights is copied, after that the training samples of MRI image has been classified into target classes in M-SVM classifier. In the second level of transfer deep learning, connected layers are trained entirely from the MRI image non target classes' pairs.

In this segmentation process, a novel technique is presented which combines CNN, M_SVM and Kernel to progress the performance of deep learning machine for segmentation of brain tumor and tumor classification. CNN contains advantages of high efficiency, fast deep learning, and only hidden layer feature extraction process. To overcome this issue, M_SVM is presented in this paper to extract and classify the hidden layer of by alternately adding layers and sub example

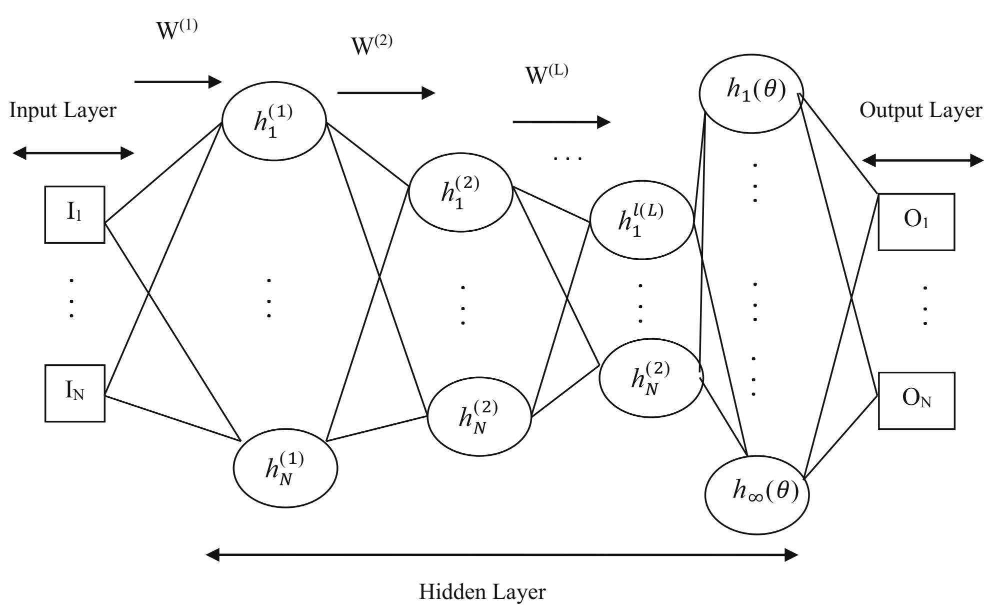

Fig. 2 Architecture of kernel based CNN

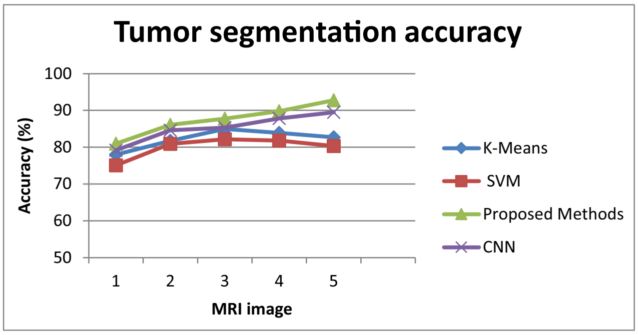

Fig. 3 Tumor Segmentation Accuracy

layers to the unique hidden layer. To tune parameters Random weights are exploited gradient. Hence, the tumor is segmented from the MRI image using the kernel based CNN and the segmented tumor is classified into benign or malignant tumor by M-SVM classifier.

Results and discussions

In this section, the performance of proposed and existing methods is estimated based on the tumor segmentation in MRI image. The proposed method has been compared with existing methods in terms of tumor segmentation accuracy, error rate and time complexity. In this comparison, a set of 40 MRI images has been utilized and these 40 images are separated into two groups normal and abnormal correspondingly. Out of the 40 MRI images, a group of 25 random patients' MRI images have been chosen when 15 normal images and 10 abnormal images are utilized for test data and remaining 15 MRI images which including 9 normal and 6 abnormal MRI images has been employed for training process.

Tumor detection accuracy

The accuracy of tumor segmentation in MRI image is depending on the tumor cells detected and segmented correctly out of total brain cells presented in brain image. The effectiveness of proposed and existing methods is tested using accuracy level during brain tumor segmentation process. The below chart 3 shows the accuracy level of proposed and existing methods

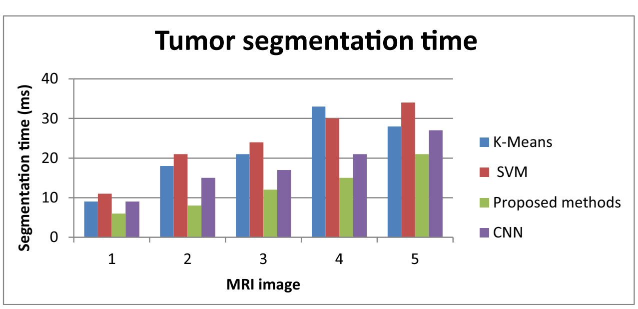

Fig. 4 Tumor Segmentation time

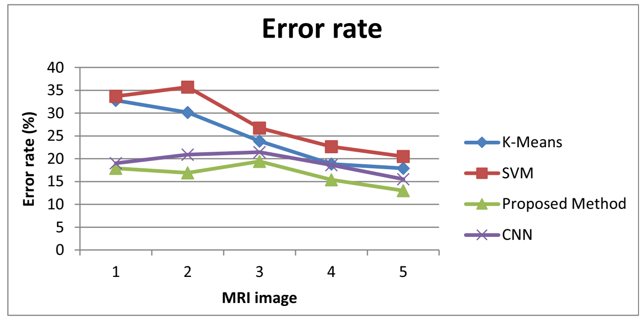

Fig. 5 Error rate of proposed and existing methods

for the segmentation of tumor using MRI image. From the below comparison chart, the proposed method having the high accuracy level to segment and classify the tumor as normal, malignant or benign in brain than the existing methods CNN, SVM and K-means (Fig. 3).

Time complexity

The tumor segmentation time is the total time to process the segmentation of tumor cells in MRI images. The time for segmentation of brain tumor has been executed in milliseconds. The tumor segmentation time of proposed and existing methods has been established in Fig. 4. From the above chart 4, it is analyzed that proposed method kernel based CNN with M-SVM has taken small amount of time to execute the tumor segmentation and tumor classification. Hence, proposed method has taken less time to segment and classify the tumor from the MRI image compared to existing methods CNN, SVM and K-Means. Thus, the proposed method has the low time complexity than the existing methods.

Error rate

Figure 5 shows the error rate of the proposed and existing brain tumor segmentation algorithms. The error rate for the tumor segmentation system has been evaluated depending on the inaccurately segmented tumor cells from the sample MRI images. From the below chart 5, the proposed brain tumor segmentation system contains low error rate in all MRI image compared with the existing methods CNN, SVM and K-Means classifier. Therefore, proposed methods can detect and segment brain tumor efficiently than the present methods with low error rate.

Conclusion

In this paper, a new deep learning method has been presented to efficient brain tumor segmentation. In this process, the MRI image has been preprocessed by combined LoG and CLAHE filtering method. Afterward, the features were extracted by

SGLDM. The MRI image has been classified into normal or abnormal brain image by M-SVM depending on the selected tumor features of brain. The segmentation was applied on abnormal brain MRI image to segment the tumor using kernel based CNN. The tumor is segmented by proposed deep learning method from MRI image effectively to give the suggestion for doctor who treats the patient. In this segmentation, the CNN has been combined with M-SVM classifier for tumor segmentation and classification. This proposed deep learning algorithm can give accurate tumor segmentation. The evaluation proposed method has effective results for brain tumor segmentation. Therefore, this method can be used to detect the brain tumor at early stage and it is helpful to avoid deaths of patient.

Compliance with Ethical Standards

Conflict of Interest The author's has no conflict of interest in submitting the manuscript to this journal.

Ethical Approval This article does not contain any studies with human participants performed by any of the authors.

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