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RESEARCH ARTICLE

CONVOLUTION NEURAL NETWORK BASED BRAIN TUMOUR DETECTION USING EFFICIENT CLASSIFICATION TECHNIQUE

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ABSTRACT

Image processing has become an essential component in many fields of biomedical research such as tumor detection, automatically determining the volume of a heart chamber, screening brain scans for possible diseases. Different techniques for automatic detection of brain tumor involve various steps: image acquisition, segmentation, classification using neural network and optimization, and identification of tumor type. This paper presents a new approach to detect and segment brain tumors. The detection and segmentation of brain tumors can be formulated as novelty detection by using Hybrid probability based straightened bound segmentation model. The main objective of the proposed method is to precisely identify the presence of tumour cells in brain images as an early indication of malignant cells that may cause to the demise of patients.

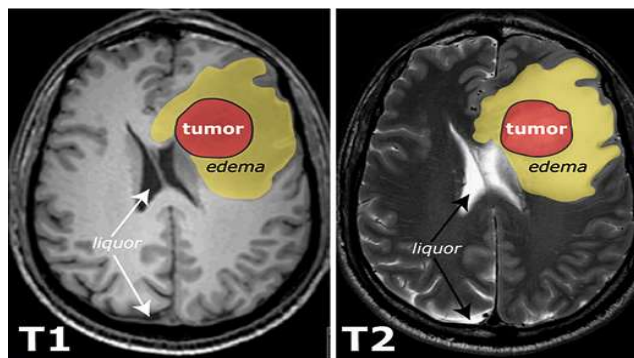
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INTRODUCTION

Many deaths are caused due to brain cancer worldwide and it has become very prevalent in recent years. Cells constitute a human body, frequently dividing to make a tissue. Generation of tumour is a process in which a cell's division starts uncontrollably outside of the orders in the brains. Brain cancer is a type of tumour which gets bigger in size and enters to other organs of body. Non-small cell brain cancer (NSCLC) and small cell brain cancer (SCLC) are the two main types of brain cancer. As non-small cell brain cancer is a more common type of brain cancer, this paper is based on the detection of non-small cell brain cancer. There's a difference between the diagnosis and treatment of non-small cell and small cell brain cancer. There are various ways to detect brain cancer by using Computed Tomography (CT) scan image, Magnetic Resonance Imaging (MRI) scan image, Ultrasound image. Image processing of necessary part of the brains is used for early diagnosis. For this, a system is developed which will help the doctors to easily detect cancer in brains from any one of the two images given as input and gives proper analysis. In this paper, CT scan image and MRI scan image are used. A CT scan or Computerized Axial Tomography (CAT) scan produces cross-sectional images of specific areas of scanned object by the use of computer processed combination of many X-ray images taken from different angle. An MRI or Nuclear Magnetic Resonance Imaging (NMRI) is an imaging technique which uses radio waves and magnetic field to form images of body. The aim of this paper is to design a system which can take any one of the two images and produces an output. The Super pixel segmentation algorithm is a powerful algorithm in terms of sensitivity, specificity and accuracy.

brain image data set, preprocessing, edge detection, morphological processing and segmentation of CT and MRI images. Every step is described in further sections.



If the cancer is detected earlier the chances of survival of brain cancer patient is more. The type of brain cancer is depended on the cellular characteristics like non small nodule and small nodule. To know the correct status of brain cancer we define the four stages as per its intensity. Staging is based on tumour size area and lymph node location. Presently, fusion of CT-MRI are said to be more effective than X-ray in detecting and diagnosing the brain cancer. The earlier the detection is, the higher the chances of successful treatment. Mostly brain cancer causes in males and females, it is caused by cigarette smoking, alcohol consumption etc. The purpose of this paper is to find the early stages of brain cancer and more accurate result by using different techniques like fusion, enhancement and segmentation

A large international study is underway to develop more powerful methods for automated classification of MR spectra based on the acquisition of large datasets of tumour spectra. Diffusion weighted imaging can help in the distinction between gliomas and abscesses, and perfusion weighted imaging can predict response to radiotherapy in low grade gliomas as well as distinguishing between different types of cerebral metastases. Intraoperative MRI has now been shown to be technically feasible, safe and effective in obtaining histological information as well as increasing the likelihood of complete resection for pituitary tumours and gliomas. Functional MRI and magnetic source imaging are alternative modalities that help the surgeon to avoid eloquent brain areas but may occasionally provide misleading information. Diffusion tensor imaging can demonstrate the effect of a tumour on white matter tracts and provides complementary information to that from other techniques that reveal areas of eloquent cortex.

Related works: Researchers in the past have investigated about this topic. Hong et al. [5] proposed an automatic system to perform the brain tumor recognition. Shape information is used to distinguish and perceive a lesion adjacent to the border of the brain and the lesion is extracted by means of Fuzzy C-means clustering technique. The proposed system performs a 3D consistency check based on three dimensional diagnoses to increase the recognition rate. This work is significant as it can help medical practitioner in focussing to the area of tumor and making it easy for classifying tumor as benign or malignant. As a result the accuracy of the C-means method and is very less, near to the actual image [2]. Choudhary et al., [7] employed fixed threshold methodology for all pixels in the image and therefore works only if the intensity histogram of the input image contains neatly separated peaks corresponding to the desired object and background. Whereas, this technique cannot deal with images containing, a strong illumination gradient. [6,7] Huang et al., proposed Extreme Learning Machine, it was a single-hidden-layer feed-forward neural network (SLFN). It had been shown that the learning speed was much faster than those of other learning algorithms such as SVM and other learning algorithms. An advantage of ELM was the randomly generated hidden layer parameters $\{w_i, b_i\}$ were independent of the training data. The ELM algorithm maps input data from the input space to the L-dimensional hidden layer feature space. Later Kernel based ELM is introduced to enhance the robustness with a regularization coefficient. In Ramanjot Kaur et al., an enhanced k-means clustering algorithm is implemented for brain segmentation in which the given dataset is classified into certain number of clusters and each cluster is provided with a centroid. Then, morphological opening was applied on the output of k-means clustering algorithm for better segmentation of cyst area in brain the image. This technique was not very effective with noisy or outlying points and with clusters of unequal sample sizes and different volume. [7].

METHODOLOGY

The main objective of the proposed method is to precisely identify the presence of tumour cells in brain images as an early indication of malignant cells that may cause to the demise of patients. Fig. 5 demonstrates the general architecture for the proposed framework. The proposed framework is sub divided into three stages: feature extraction, filtration, segmentation.

Pre-processing: The proposed algorithm is tested based on the classifier on the region of suspicious tumour of each slice. different contrast and CT images also contain procedure noise. The contrast adjustment is done simply by normalizing the window level and range around brain intensity histogram. Moreover, in order to reduce the noise level Gabor filter is adopted. The filtered blocks are then returned to their original positions. Because these blocks overlap with each other, many different estimates were obtained for each pixel.

$$rout = 4 + \frac{L}{2}, rin = rout/2, if(L \geq 10) \dots\dots\dots(1)$$

And

$$rout = 2 + \frac{L}{2}, rin = \frac{rout}{2} - 1, if(L < 10) \dots\dots\dots(2)$$

Where,

L is the length of the longer side of the filtered image. If the shape of a tumour candidate is approximately spherical, then a major portion of the tumour region is bounded by the circle Lin and the edge of the tumour is between the circles Lin and Lout.

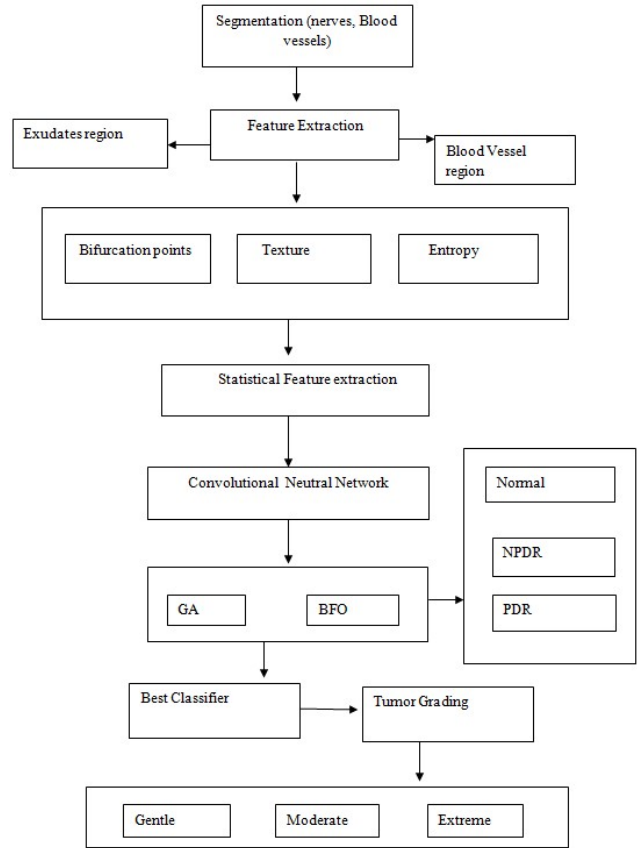


Figure proposed architecture

Histogram color feature extraction: In the color feature extraction normalized Histogram and Discrete Cosine Transform are used. In the Histogram methods, the reference image is compared with each image block in terms of its histograms. The difference between the individual peaks is taken and the mean squared difference is determined. Each block with relatively smaller difference matches the template and hence can be extracted as part of that texture. If the difference between the template and the current block is smaller than a particular threshold, then that feature is marked YES for that particular block. As in the case of color, we also evaluated the performance of these methods and found that for the training image the Histogram with bins method was the most accurate.

Kernel classifier: In the proposed hybrid kernel ELM, a positive regularization coefficient is introduced in order to make the learning system more stable. Assume $H^T H$ is non singular, the coefficient $1/\lambda$ is added to the diagonal of $H^T H$ in the more stable and with better generalization performance. We then can have,

$$\beta = H^T \left(\frac{1}{\lambda} + HH^T \right)^{-1} e - 1$$

$$f(x) = h(x)\beta = h(x)H^T \left(\frac{1}{\lambda} + HH^T \right)^{-1} e - 1 (T)$$

The output function can be written as,

$$f(x) = h(x)H' \left(\frac{1}{\lambda} + HH' \right) e - 1 (T)$$

The hidden layer feature mapping $h(x)$ need not to be known to users, instead its corresponding kernel $K(u, v)$ can be computed. Here the Gaussian kernel is used, $k(u, v) = \exp(-\gamma\|u-v\|_2)$.

The enhanced kernel ELM was designed for two class classification and regression. However when only one class data is used for ELM training, it is showed one class classifier.

- 1) Let's assume $t_j=1$, which means only one class data is used for training. The result β becomes a linear approximation mapping $g(\cdot)$ to T .
- 2) In geometry, it is a hyper plane approximation. Then it can be shown that the difference $|f(x)-1|$ is the distance of any point (a sample, in either class) to the hyper plane constructed by the ELM.
- 3) Thus if the hyper plane can be used to represent one class, any point away from the plane will indicate that it is not in the same class, which means we can use it to detect novelty.
- 4) In the original ELM, as it is only a linear transformation, the one-class mapping is not represented accurately using the hyper plane. The detection result is thus not satisfying. With the hybrid kernel transform the data is mapped to a higher dimension space, similar to many other kernel methods.

Convolutional neural network: When a network is used as a classifier for a problem with classes c_1, \dots, c_m , the output layer contains one neuron per class, forming a vector $a = (a_1, \dots, a_m)$. The Max function is used to convert these values into probabilities, where $\text{Max}(a_i)$ is the probability of the input to belong to class c_i . Therefore, for each instance we intend all the output neurons to produce values close to zero, except the neuron of the correct class, which should be close to one. The activation function used to model non-linearity is usually the Rectified Linear Unit (ReLU), which can be computed faster than the traditionally used sigmoid or hyperbolic tangent functions, and also offers interesting convergence properties.

Ptimization: It considers an approximate of variable and the matching solution as initial resolutions. Any estimation of sigma has been selected as the initial variable and the matching fitness function which is the normal exactness over the three folds of NN classifier is processed. In the generation function, different cases (runs) of the variable sigma are produced and a matching bit string is produced. A cross over points is selected and the bit function is partitioned into two sections. Two parts of bit strings really belonged to various strings are employed to finish cross over operation. A certain rate of strings is connected with cross over operation only and rest are left unaltered. Small amount of function in mutation probability are characterized and also given subsets of strings which was selected from the cross over function. A given bit position is selected for cross over function and the matching bit is flipped. Again all new strings are examined with the matching fitness function capacity. The strings with grater fitness function capacity are held and strings with less fitness function capacity are rejected. This completes single generation. The procedure is continued for so many generations until it achieves the very higher fitness function value of the strings and hence it enhances the system.

Analysis: The performance of the algorithm is evaluated using the measures like accuracy, sensitivity, specificity, positive predictive value or precision and negative predictive value defined as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{FP + TN}$$

TN=True negative
 TP=True positive (carcinoma cases are correctly classified as (TP))
 FN=False positive ((FN))
 FP=False positive

Table 1. Comparison of extraction features

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)
Enhanced HMM	97.21	94.09	95.87
Contourlet features	94.3	92.1	91.4
Wavelet features	88.6	91.4	85.7

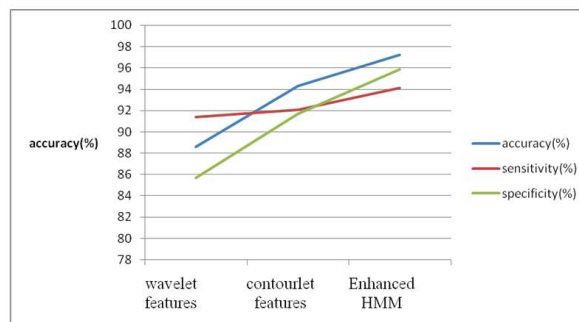


Figure 4. Performance analysis of extraction features

Table 2. Performance comparison of classifiers (accuracy in %)

Types of tumors	SVM	LSSVM	Enhanced hmm
Astrocytoma	76.97	77.18	80.02
Chordoma	85.79	85.91	86.29
Craniopharyngioma	84.38	87.50	91.63
Meningioma	89.88	98.91	98.91
Ependymoma.	95.85	95.19	94.89
Medulloblastoma	72.14	72.00	79.61

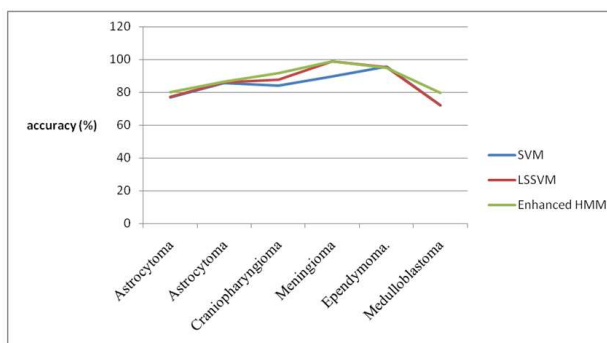


Figure 5. Performance analysis of classifiers

CONCLUSION

In this paper, the proposed framework for identifying tumor cells in the various phases have been presented. In this System, it is consists of four stages such as preprocessing, segmentation, feature extraction and classification, have been proposed. The preprocessing stage extracts backgrounds pixels to empower the working on further stages on the foreground pixels only. In the segmentation process the threshold method is carried out whereas region growing is adopted here. In the region growing methods, the evaluated sets are very small at the start of the segmentation process. After segmentation, the feature extraction had done it shows that the proposed method have high accuracy than counterlet, wavelet, wavelet methods. The extracted images are then classified by using the best classifier, however the is used here. Thus the stimulation results had displayed that proposed system results an average accuracy of 97.56%

sensitivity of 94.09% and Specificity of 95.87% respectively. Thus the proposed modal had enhanced the overall performance and increases the efficiency of the system. Hence the proposed methods is significant than the previous methods and it can be utilized as an efficient diagnostic tool by the clinicians during the detection of tumor cells

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