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Non-Invasive Diagnosis of Human Brain Tumors: A Review.

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ABSTRACT

Phenomenal advancement in the brain diagnostic imaging have been made during the past few decades. The blooming of new imaging techniques and constant improvement in the display of digital images have expanded the study of brain anatomy and pathology. This paper illustrates the comprehensive assessment and performance overview of various diagnosis techniques of human brain tumors such as positron emission tomography, magnetic resonance imaging and computed tomography and the new methods that have been developed to improve the performance of these existing human brain scanning techniques. In this paper we will also discuss about the merits and demerits of these new techniques. Further the paper also evaluates the different techniques that are developed to improve the efficiency of the segmentation of human brain tumours imagery. The paper would also emphasis on the three dimensional imaging techniques that gives us complete and handful structural information about one's composition that could act as assistive system for the diagnosis and restorative purpose in healthcare and medical domain.

Keywords: brain tumor, brain scanning techniques, computed tomography, magnetic resonance imaging, discrete wavelet transform, Bayesian Neural Networks.

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INTRODUCTION

Brain tumors are among the major causes of tumor-related deaths globally. Therefore considerable research effort is being done to improve the patient outcome. Although there are many imaging techniques available for the study and management of brain tumors for clinical practices, nevertheless they have their own advantages and limitations. The assessment of tumors using multiple imaging techniques is now one of the upward trends in neuroradiology, where MRI, CT and molecular imaging techniques play a key role and is much more instrumental in the brain tumor diagnosis [1].

There are various tests available for diagnosing the brain tumours which will not only be able to assist the experts to know the type of tumour but also helps to get answers for what, how, when and whereabouts of the disorder [2]. Brain tumors are classified as primary brain tumors that originate in the brain or secondary brain tumors which originate elsewhere. Primary brain tumours usually do not spread beyond the brain cavity or spinal canal but they have a tendency to intrude on spaces occupied by healthy tissue. On the other hand secondary brain tumor originate in different organs other than the brain but later spread and enter the brain. Secondary brain tumor cells have a different origin but as they grow they start getting deposited in the brain system through the lymph and circulatory systems. The most common cancer types that lead to secondary tumors in the brain include malignant melanoma, lung cancer, kidney cancer, breast cancer, and colon cancer.

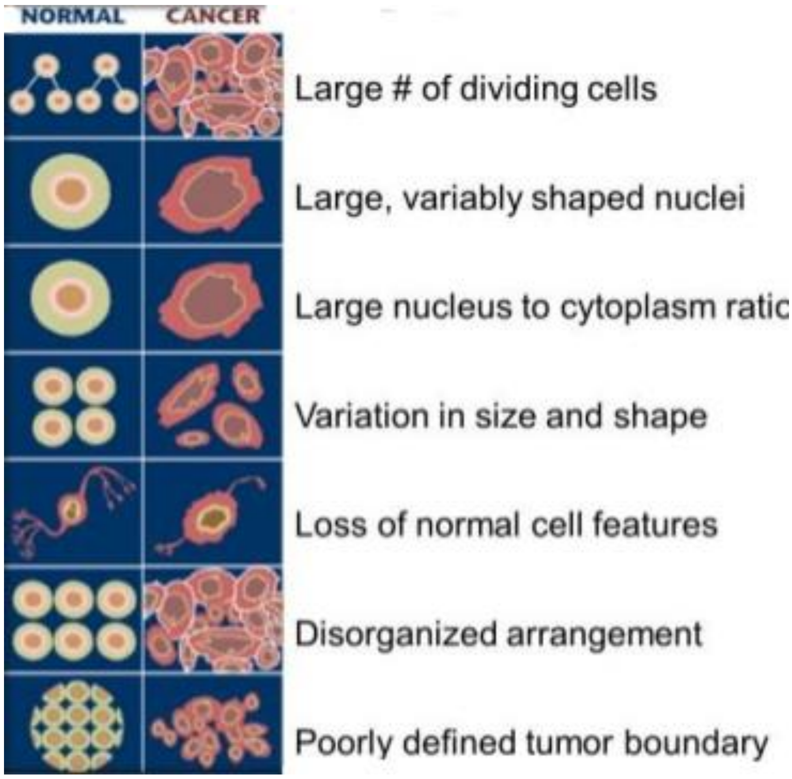

Fig. 1. Microscopic appearance of normal and cancer cells.

On the basis of the behaviour of morphologically and functionally altered cells, brain tumors can be classified as either malignant or benign. The main difference between the malignant cells and the benign cells is that in malignant cell the normal process of division known as mitosis goes uncontrolled. These cells excessively vary in shape and size. Such belligerently growing cells moves the normal tissue cells aside and invade more space by squeezing them. The distinct feature of malignant tumors is Metastasis i.e. spreading beyond their original location [3].

The diagnosis of brain tumor highly depends on the non-invasive techniques as the diagnosis is an extremely complex and sensitive clinical task. In this paper we would be discussing briefly about different types of current scanning techniques along with some new techniques used for segmentation of the brain image with its merits and demerits. Based on the critical analysis, we have tried to propose new methods to improve the existing scanning techniques.

Types

Computed Tomographic

Computed tomographic images are widely used for the identification of abnormal brain tissue following infarct and haemorrhage in stroke [4]. Computed tomography combines an x-ray type device with a computer. In Computed tomography scanning the patient lies on a table that slides into a ringed-shaped opening in a scanning circle so that x-ray reading penetrate the brain from various direction. Thousands of x-ray reading are then fed into the computer, which brings the information together into a picture of the brain. Structures and lesions previously impossible to visualise can now be seen with remarkable clarity [5].

Currently manual lesion delineation is the standard approach, but it is both operator-dependent and time-consuming. To confront these issues, a new method that can automatically delineate infarct and haemorrhage in stroke CT images has been developed. The key elements of this method are the accurate normalization of CT images from stroke patients into template space and the subsequent voxel wise comparison with a group of control CT images for defining areas with hypo or hyper intense signals. This approach is very effective in reconstructing lesions resulting from both infarct and haemorrhage and yields lesion maps spatially consistent with those produced manually by expert operators. A limitation of this new method is that, there is reduced sensitivity in the automated method in regions close to the ventricles and the brain contours. However, the automated method provides a number of benefits in terms of offering significant time savings and the elimination of the inter-operator differences inherent to manual tracing approaches. These factors are relevant for the creation of large-scale lesion databases for neuropsychological research.

The automated delineation of stroke lesions from CT scans also enable longitudinal studies to quantify changes in damaged tissue in an objective and reproducible manner. But still manual tracing methods remain the standard technique for delineating damaged brain regions; however automated delineation approach has many important advantages such as it is fully automated, produces lesion images in a common Montreal Neurological Institute [MNI] space which is useful for lesion symptom mapping, can deliver significant time savings and eliminates inter-operator differences that are intrinsic to the manual approach [6].

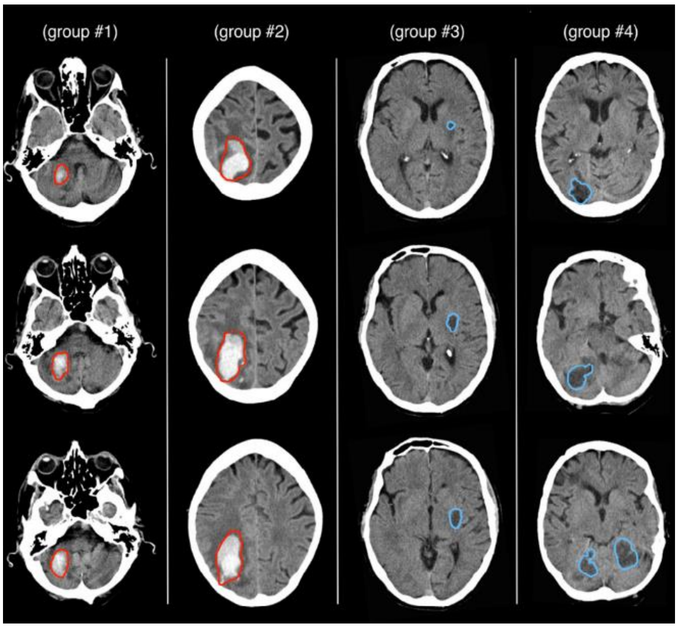

Fig. 2. Brain lesions obtained by the automated method on four different cases, each belonging to a different group: group 1, focal haemorrhagic; group 2, extended haemorrhagic; group 3, focal ischemic; and group 4, extended ischemic. Blue and red outlines region define the lesion area and correspond to significant positive and negative increases, respectively [4]

Positron Emission Tomography (PET)

This is most versatile and unique imaging technique widely and generally known as Positron Emission Tomography which is a non-disturbing imaging procedure adopted by all the practitioners and radiologist across the world. It provides the images at molecular level with the aid of physically beleaguered radiotracers with great sensitivity. Informative knowledgeable and detail quantitative information about variety of syndromes and health factors can be extracted from usage of PET imaging. It is often used to assess and quantify the information about contagion, swelling and cancer by identifying and decoding photons from the radiotracer localized to abnormal cells. Image processing techniques such as segmentation methods play a vital and important role in PET images in order to discriminate and distinguish abnormal tissues from surrounding areas. Hence, correct and appropriate image segmentation methodologies are much more important for planning disease detection, diagnosis of patients and correct treatment.

The ultramodern segmentation methods for Positron Emission Tomography images, their assessment, quantification and lately established advanced Positron Emission Tomography image segmentation techniques are thoroughly interpreted and synthesised. The methods or techniques are further segregated into boundary-based, manual separation, thresholding-based, stochastic and learning-based, region-based, boundary based and joint based segmentation methods. These classifications are shown in. figure 3 [7-9].

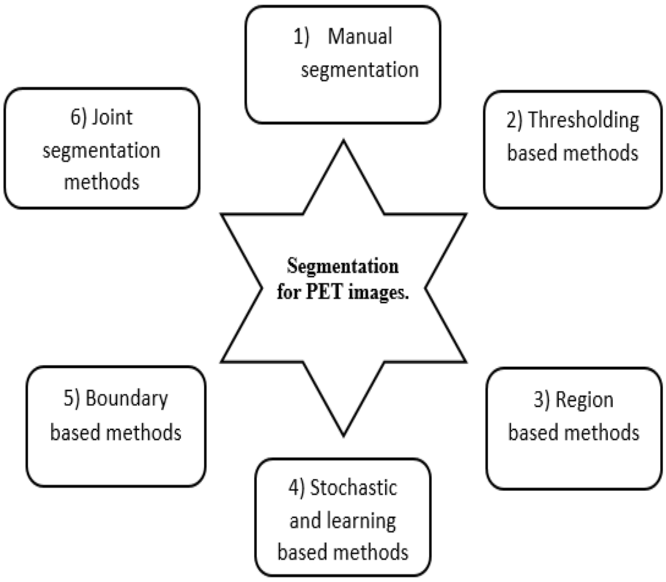

Fig. 3. An overview of the categories of PET segmentation methods.

Radiotracers

Radiotracer plays crucial and key role in the Positron Emission Tomography imaging technique. In Positron Emission Tomography a radio-pharmacy compound is designated with a biological active ligand to form a radio tracer. This radiotracer is then injected or immersed into the patient's body. The PET scanner records and measures the distribution and dispersion and congregation of the radiotracer accumulated throughout the patient's body as a function of time t. To achieve this Positron Emission Tomography uses positron emitting radio isotopes as molecular examinations so that the biological progression can be studied through imaging in vivo. As of now many radio tracers have been developed and among them fludeoxyglucose is considered the most common radiotracer for studies. Concurrently, a large number of radio tracer amalgams have been developed which have some benefits over fludeoxyglucose such as these tracers do not gather in the heart/kidney or any other organ. However, fludeoxyglucose is still the furthermost frequently used radio tracer in the Positron Emission Tomography imaging procedure [10].

Challenges in PET imaging

There are two related task that can be thought of with image segmentation: recognition or identification and delineation and allocation. Recognition or identifying is the process of distinguishing where the object is and to differentiate it from other object like objects in the image, and allocation is the action of unfolding the spatial extent of the object region in the image. High acceptance regions are perceived and acknowledged by the radiologists in the recognition progression. These rough areas of where the object are positioned in the image are measured as region of interest. Then delimitation, which is the second step of subdivision. The parting of the uptake region from the background and unrequired uptakes is the main aim of Positron Emission Tomography imaging. But due to some intrinsic and extrinsic factors the segmentation in Positron Emission Tomography imaging gets highly effected. These factors are:

- Issues and Constraints related to resolution.
- Large variation in the texture and shape
- Noise Interference and distortion.

With the increase of these factors the striving of subdivision increases in many ways. For instance, a patient under the scan are at times incapable to grip their inhalation during the entire scanning time, and motion artefacts may occur that may further blur the images. Next issue is due to the large unpredictability in shape or smoothness of the pathologies. The dissection issue becomes more perplexing due to difficulty in specifying the existing methods for such cases. Noise in and images is highly stirring and it lead to many complications in image segmentation [10].

Magnetic Resonance Imaging (MRI)

Magnetic resonance imaging is a furthermost prevalent imaging practice for human body imaging. Magnetic resonance imaging gives a high degree of resolution and accuracy about the state of the brain. Post processing of brain Magnetic resonance images need algorithms for, detecting the abnormalities in the brain of a patient being examined. It has been seen that in both clinical diagnosis and in biomedical research high quality Magnetic resonance imaging is routinely used for obtaining the anatomical structure of the brain. Magnetic resonance imaging is basically a non-invasive technique that provides characteristics like high spatial resolution, superior soft tissue differentiation and better contrast. The best part of Magnetic resonance imaging is that it does not root any radiation protections to the tissues of the patients as it is not using any damaging ionizing radiation.

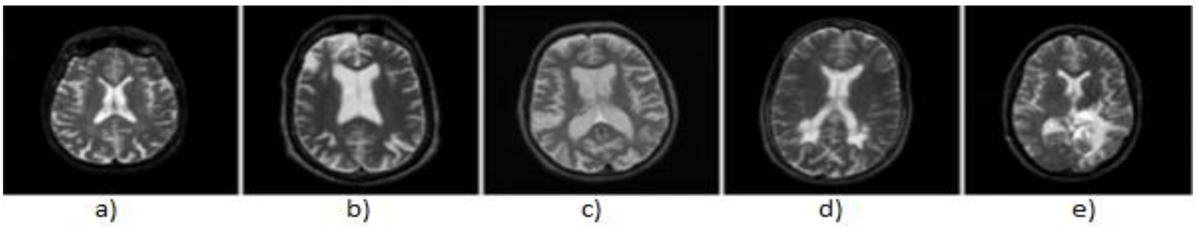

Fig. 4. MRIs with a).normal brain, b). Stroke, c). Degenerative disease, d). Infectious disease, f). Brain tumor [11].

The cataloguing of normal obsessive brain circumstances from Magnetic resonance imaging is important in biomedical domain as MRI attentions on soft tissue anatomy and engenders a large statistics set and particulars about the subject's brain situations. However, manual elucidation becomes difficult due to high dimensions of data. Thus, there is a stipulation to develop an automated image scrutiny tools.

It is seen that the feature extraction from MR brain images can be passed out by exploiting several popular signal/image analysis approaches already available, e.g. Fourier transform based procedures, independent component analysis and wavelet transform based techniques etc. The wavelet transform based procedure has become the most preferred image analysis and grouping problems because this technique is good for mining frequency space information from non-stationary signals. By fine-tuning the wavelet in the selected sequence the resolution of the analysis can be measured.

The classification of Magnetic resonance imaging images of normal and under examination brain conditions poses a lot of encounters from technological and scientific point of opinion, as Magnetic resonance imaging emphases on soft tissue anatomy and generates a large data set and which acts as the conditions of the brain. An advanced slant is built by collaborating wavelet entropy based spider web plots and probabilistic neural network for the cataloguing of Magnetic resonance imaging of brain images. The method is classified into two steps [1] wavelet entropy based spider web plots used for feature extraction and [2] probabilistic neural network for the classification. Here the spider web plot is a geometric construction pinched using the entropy of the wavelet approximation components. Whereas, probabilistic neural network is used to achieve an accurate classification of patterns [11-13].

Wavelet transform based feature extraction

The most common approaches for abstraction feature from Magnetic resonance images are independent component analysis, Fourier transform and discrete wavelet transform. The DWT is the natural mathematical contrivance of choice when it comes to viewing digital images from a single modality. Furthermore, DWT provides influential insight into an image's spatial and frequency features. In addition to that it is also efficient and highly intuitive framework for the illustration and storage of multi resolution images. The Fourier transform offers representation of an image based only on its frequency content. Hence this representation is not spatially localized while wavelet functions are localized in space. The biggest advantage of DWT over FT is that DWT decomposes a signal into a hierarchy of scales stretching from the coarsest scale and FT decomposes a signal into a band of frequencies. Therefore wavelet transform is a better contrivance for feature extraction from images as it offers illustration of image at various resolutions [11].

Spider web plot

The spider web plot is a conceptual management tool. It consists of a sequence of equiangular spokes, called radii, with each spoke signifying one of the variables. The length of a spoke is relative to the magnitude of the variable it epitomizes. A line is drawn connecting each spoke to the next one. The resultant drawing looks much like a spider's web. The spider web plot can be used to evaluate whether there is similarity between the observations and whether there are outliers [10].

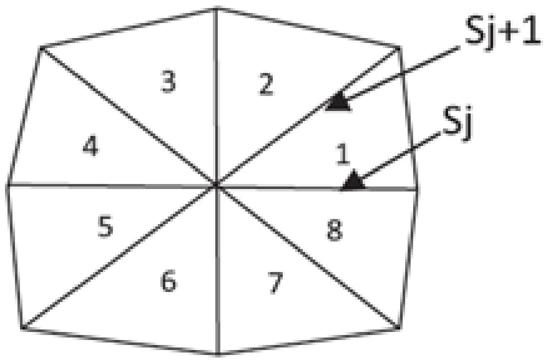

Fig. 5. Shows the construction of spider web plot. The variables Sj, Sj + 1. . .etc. indicates the values of entropy of the wavelet approximation component of an image for the 8 scales of decomposition [11].

Probabilistic neural network (PNN)

Probabilistic neural network methodology is used for the cataloguing of images into normal and abnormal modules. It is a kind radial basis network suitable for pattern cataloguing complications. PNN also provides general solution to the pattern classification problems.

The network categorizes the input feature vector into a specific class because that class has the maximum probability to be correct. PNN has two layers- Competitive Layer and Radial Basis Layer are the two widely adopted. Just after an input is inserted, the distance from the input vector to the training input vectors is computed by the first layer which produces a vector that indicates the closeness of training input to inserted one. To get a gross output as a vector of probabilities additional layers contributes for each class of input. Lastly, modest layer transfer function on the output of the second layer picks the maximum of these probabilities, and gives a 1 for that class and a 0 for the other classes [11-13].

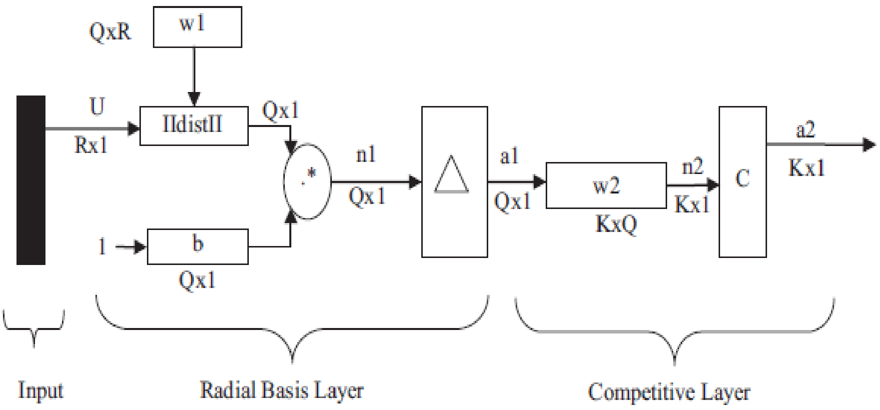

Fig. 6. Probabilistic neural network structure [11].

In Fig. 5, these symbols and notations are used by MATLAB_ Neural Network Toolbox™. Dimensions of arrays are marked under their names. The input vector, denoted as U, is presented as the black vertical bar in its dimension is Rx1. In the radial basis layer, w1 is the weight matrix with dimension QxR where Q is the number of neurons in the layer, b is the bias vector and a1 is the output vector. In the competitive layer w2 is the layer weight matrix and a2 is the output vector. K is the no. of neurons in the layer which tells the no. of classes of input data. The output vector of radial basis layer a1 is first multiplied with layer weight matrix w2 producing an output vector n2. A linear activation function is used in the competitive layer. The competitive function denoted as C in Fig. 5 produces the output a2 corresponding to a1 which is the largest element of n2, and 0's in another place [11].

This methodology is used for the getting the following purpose:

- Acquiring the image or data.
- Choosing the proper wavelet for analysis.
- Calculating the entropy of the wavelet decompositions.
- Calculating areas of the spider web plot.
- Constructing the spider web plots using entropy values.
- Performing statistical analysis of the areas.
- Classification using probabilistic neural network with suitable areas as feature set [11].

Fuzzy anisotropic diffusion based segmentation

This is a programmed dependable method used for the identification of the brain tumor, its multi-stage scheme and for abstraction of tumor region. This system categorizes and fragments the brain tumor in numerous segments. Shows the particulars of the scheme. The grouping of MR images into normal and cancerous images is done and they are provided to the system for identification purpose. Initially, noise removal is done from these images. After noise and attenuation dismissal texture features are taken out from these images [14]. Then the features are inserted to the ensemble based Support vector machine. Cataloguing is done using weighted majority voting. For enhancing the weights GA is applied.

Adoption of the above practise in this scheme helps to achieve increased accuracy for classification. At the end the images are classified [15]. Splitting up is a process involving several steps where the skull part is removed, the brain portion is abstracted and then tumor portion is mined from this dig out from the abstracted brain portion, using the fuzzy c-Mean clustering technique [16].

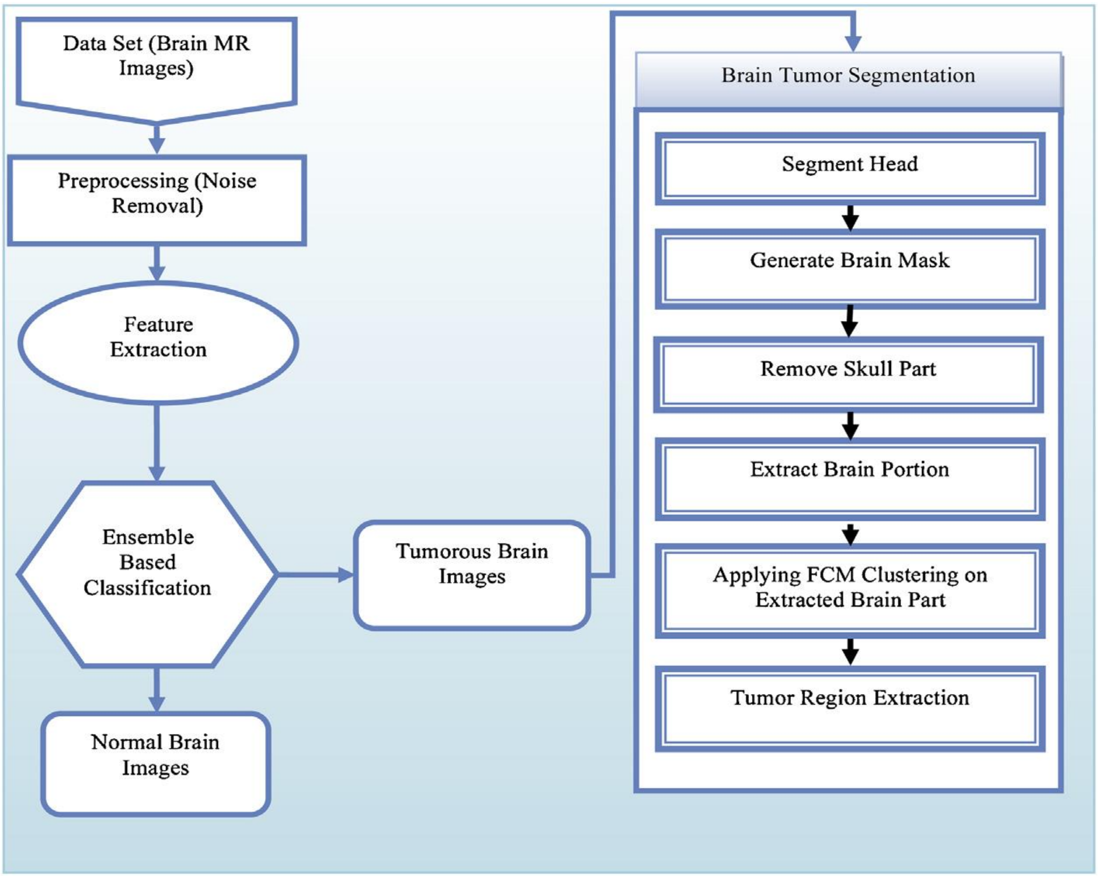

Fig. 7. Fuzzy anisotropic diffusion based segmentation and texture based ensemble classification of brain tumor method [17].

Adapting this practise helps in precise mining of the tumor region and accurate segmentation results of the projected system. This further helps in correct abstracting of the tumor region from the brain MR image. This technique thus helps in furnishing the precise details of the tumor type, its size and its thickness [17].

Segmentation techniques for Brain tumor images

The segmentation of brain tumor comprise of distinguishing the diverse tumor tissue from normal brain tissue. The uncovering of abnormal tissue may be stress-free in brain tumor studies most of the times. But, precise and reproducible segmentation and depiction of abnormalities are convoluted. Many significant investigations in the arena of brain tumor segmentation have been steered in the past by researchers in the fields of soft computing and medicinal imaging. Finally, both semi-automatic and fully automatic approaches have been projected. Ease of the splitting up and degree of user supervisor are the main key factor for scientific acceptance of segmentation practises. Presently, Interactive or semiautomatic methods are prevailing in medical practice, specifically in application where erroneous are insupportable [18].

Another technique is Magnetic Resonance Spectroscopy. In this consignment, radiology professionals are likely to get benefit from the support of computer-based systems built around vigorous cataloguing processes. The collective method yielded very reassuring results in terms of diagnostic discriminatory binary sorting using Bayesian Neural Networks. In most cases, the classification correctness enhanced on previously testified results.

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Gaussian Decomposition and Bayesian Neural Networks

The main purpose of the Gaussian decomposition signal processing technique is to break down a given Magnetic resonance imaging spectrum into its constituent tones, represented by coefficients of amplitude, standard deviation and translation of their corresponding Gaussians. Subsequently, the conformation of the metabolite peaks is provided by the Gaussian decomposition. Simultaneously, it alleviates the problem of metabolite-associated broad amplitude peak overlapping between metabolites resonating at similar frequencies, overcomes the noise and baseline problems, and eases the subsequent feature selection and the classification processes. These coefficients obtained by GD, in conjunction with the axis of transformation and the concatenation of amplitude and standard deviation DIM's, are used for the discrimination between different types of brain tumours on the basis of their MR spectra. The obtained diagnostic classification results are very encouraging and rank among the best obtained to date using alternative methods to analyze similar data.

This pattern has an exception due to the involvement of some super-class group This could be due to the calculation of the exact variations of the translations of each Gaussian in each tumour class of the experiments, so that, when several tumour types are merged in a group, the difficulty of calculating the exact translation of the metabolite increases. Resulting in accumulation of error for each pattern, making the process of feature selection inconvenient and, subsequently, affecting classification negatively. Now, by making a transformation of the amplitude and standard deviation vectors, so as to expand the area of each one translation component, smoothing the effect of variation in translations this problem is overcome. The practical implication of this method and the results of its application to a number of brain tumour classification problems is straightforward. Furthermore, alternative and more exhaustive feature selection and classification methods can be used in combination with GD can be investigated [19-20].

Kernel feature selection for brain tumor segmentation.

Brain tumors have a large grouping in profile and presence with deliberations. To resolve this vagueness multi-spectral images have the benefit in providing matching information over it. However, they may also bring along a lot of dissection errors, redundant evidence and increases the data treating time. Thus to make multi-spectral images effective it must be bonded to extract the most useful features to obtain the best dissection with the least cost in time. That is done with the assistance of the support vector machine classification assimilated in a kernel space with the choice of features. The choice criteria's are well arranged by the kernel class separatibility. Support vector machine classification is used to follow up the brain tumor fruition, that follows the given steps: 1) It studies the brain tumor to select the features from the Magnetic resonance imaging for the investigation of the affected person; 2) to robotically segment tumors in data by using support vector machine; 3) to enhance the tumor contour by a region growing practise. This system has given very nourishing results on testing it on real patient images [21-22].

Bounding box method using symmetry

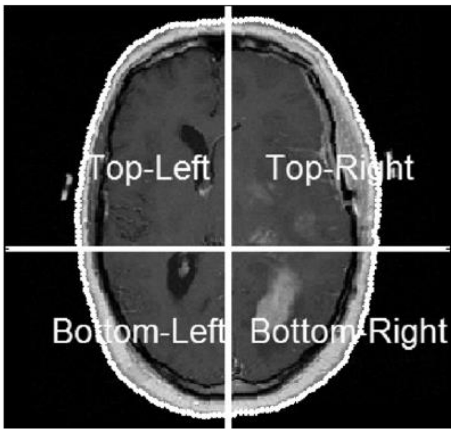

Fig. 8. Vertical line represents geometric axis of symmetry [23].

The indexing of patient's databases according to dimensions, position and other features of the brain tumor is an important therapeutic task. This task requires segmenting the tumor within the image from diverse MR modalities. Till date, computerised segmentation of brain tumor from MR modalities leftovers a challenging, penetrating task. The Bounding Boxing technique is a fast, automated and estimated segmentation technique. It works on the basis on an unsupervised change detection method that highlights the distinctions between the right and the left part of a brain in an axial view of an MR slice. This detection uses a very original score function that is based on Bhattacharya coefficient along with histograms of grey level intensity [23].

FUTURE TRENDS

With the advancement of computational intelligence and machine learning techniques, computer-aided detection attracts more attention for brain tumours detection and identification. It has become one of the major research subjects in medical imaging and diagnostic radiology. Computer-aided detection/diagnosis systems can enhance the diagnostic capabilities of physicians and reduce the time required for accurate diagnosis.

There are many methods that can be collaborated with Computer-aided detection/diagnosis to improve its efficiency. Such computational methods are; the feedback pulse-coupled neural network for image segmentation, the discrete wavelet transform for features extraction, the principal component analysis for reducing the dimensionality of the wavelet coefficients, and the feed forward back-propagation neural network to classify inputs into normal or abnormal. These proposed techniques demonstrates its effectiveness compared with the other machine learning recently published techniques. There are several future directions which might further improve the Computer-aided detection/diagnosis systems for human brain MR images: 1) the acquisition of large databases from different institutions with various image qualities for clinical evaluation and improvement in the Computer-aided detection/diagnosis systems 2) improve the classification accuracy by extracting more efficient features and increasing the training data set. 3) There is still much room for additional researcher to utilize other machine learning techniques and integrate them into a hybrid one system. 4) Further experiments and evaluation are therefore desirable to establish whether the proposed approaches have generic applications [24].

CONCLUSION

In Computed Tomographic imaging manual tracing method remains the standard technique for delineating damaged brain regions, nevertheless the discussed approach has important advantages: it is fully automated, produces lesion images in a common MNI space which is useful for lesion–symptom mapping, can deliver significant time savings and eliminates inter-operator differences that are intrinsic to the manual approach. Positron Emission Tomography imaging technique offers quantitative applicable information on the cancerous brain while the image segmentation helps in retrieving the various relevant information. But PET imaging suffers from many factors like noise, resolution related issue, variability in the shape, texture etc. These factor thus makes segmentation difficult in many ways. For Magnetic Resonance Imaging the above discussed approach consists of two steps: feature extraction and classification. For feature extraction, wavelet entropy based spider web plots is considered which results in great reduction in features. The probabilistic neural network provides a general solution to the pattern classification problems and the accuracy achieved is very good in detecting normal images and degenerative disease images. In segmentation techniques of brain tumor images Gaussian Decomposition provides information about the conformation of the metabolite peak and overcomes the noise and baseline problem and eases the subsequent feature selection and classification processes. While in Kernel Feature selection technique the challenges due to lots of unwanted information, accelerating the data processing time and error while segmentation are overcome. Furthermore, with the advance of computational intelligence and machine learning techniques, computer-aided detection attracts more attention for brain tumor detection.

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