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A Survey on Brain Tumor Diagnosis and Edema Detection Based on Machine Learning

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Abstract. Early brain tumor diagnosis has a significant role in reducing the risk of disease, as well as led to get better treatment results. Usually, magnetic resonance imaging (MRI) images are evaluated manually through visual inspection, which is difficult, time-consuming and often erroneous; this process is performed by radiologists or clinical experts, and its accuracy depends on their experience. Recently, computer-aided diagnosis (CAD) becomes very essential to overcome these limitations. This paper provides a comprehensive assessment of the existing techniques and methodologies for automated detection of brain tumor coupled with oedema detection methods utilisation, with an emphasis on machine learning models. Moreover, this paper provides an analysis of the integrated procedure that pertains to the retrieval of brain pictures by identifying particular data sets in the procedure to recognise the stipulated attributes.

1. Introductions

This portion of the research provides a comprehensive assessment of the existing techniques and methodologies used in medical image segmentation. This paper also incorporates a comparative review of automated brain tumour coupled with oedema detection methods utilisation. Moreover, additionally provides an analysis of the integrated procedure that pertains to the retrieval of brain pictures by identifying particular data sets in the procedure to recognise the stipulated attributes. asserts that the use of a computer-aided analysis in medical imaging affects the decision-making ability of experts in providing accurate



images that are relevant to existing distance and volume [1-2]. Also asserts that detecting brain ailments remains challenging among neurologists and radiologists because of the existence of related brain abnormalities [1]. The variations in the presence of these abnormalities affect the extent of challenges experienced by the experts with respect to the tasks because of the existence of differential analysis coupled with the intricacy attached to physical segmentation [3]. The procedures delimit the precision levels causing the identification of the requirement for the provision of more time considered essential in meeting the specific needs of the procedure. The process requires the integration of extensive procedures necessary in the identification of accurate and consistent techniques necessary in providing the solutions related to existent questions. This portion of the research seeks to integrate a descriptive analysis, which provides a description that recognises the existent requirements pertaining to automatic detection. The methodologies will affect the evaluation procedures integrated relating to the existing human brain abnormalities which include injuries, oedema and tumour. The procedure is also helpful in the identification of other abnormalities that can be obtained from computerised pictures of the human brain. In this work, the attention was given to four categories of machine learning these categories are Region-based methods, Neural Networks Based Methods, Fuzzy Based Methods and Threshold-based methods. The remaining part of this work is organized thus: Section 2 discussed 2. Medical image segmentation while section 3 described various machine learning-based techniques. Section 4 presented the conclusion of the review.

1.1. Brain Tumour

In certain indeterminate situations, the cells of the brain may grow in an uncontrolled way, which delimits the ability of the regulating function of the regular cells causing further uncontrolled brain cell growth [4 - 5]. The malformed mass that is developed due to the uncontrolled growth is diagnosed as the brain tumour and it grows inside the skull region, which affects the normal brain functioning by causing an increased heaviness on the brain. The increased burden on the brain initiates a shift among brain tissues, which pushes the tissues towards the skull region causing more nerve damage in the healthy brain portion [4], [6]. These brain tumours may be classified as being either malignant, which means they are cancerous or benign, which means they are non-cancerous as shown in Figure 1, which shows the position of the tumour by the stipulation of the origin site [4], [7]–[9].

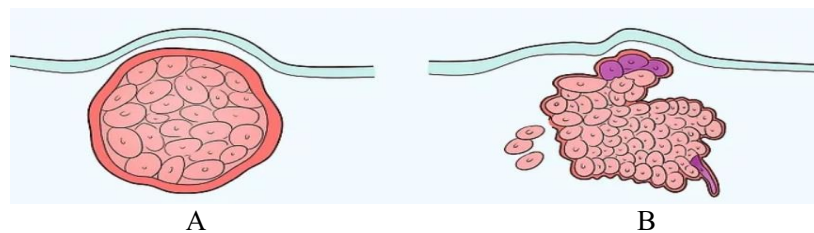


Figure 1. Types of tumour: (A) benign tumour and (B) malignant tumour

1.2. Brain Edema

Cerebral edema (or oedema) signifies the level of fluid build-up in the regions external and internal to the brain. The detection of any variations related to cerebral oedema leads to the detection of the variations related to the brain as it becomes smooth and soft, which causes the overfilling of the cranial cave. The process also causes narrowing of the sulci (grooves), flattening of the gyri (ridges) and it results in ventricular cavity compression. This abnormality may be detected through the presence of different symptoms such as nausea, vomiting and, in serious cases, coma and seizures. In the case of herniation, the person may undergo respiratory symptoms and possible arrest of the respiratory tract which is attributed to high compression of the respiratory control centres in the pons as well as medulla oblongata.

2. Medical image segmentation

Maintaining that the segmentation of brain tumours includes a process that aims at distinguishing different tumour tissues. Most studies on brain tumours suggest that detection may be influenced if abnormal tissues are present. Nevertheless, providing precise and duplicable segmentation is complex since the prevailing abnormalities include a complex process. The combined knowledge from several previous studies has been used to attempt the enhancement of medical imaging techniques required for the betterment of brain tumour segmentation. Fully automatic techniques have been suggested because of the increasing requirement for more efficient procedures [4], [10]. A major portion of the segmentation methods considered clinically standard has relied on the straightforward segmentation concerning the present extent of degree supervision. The present work details the most significant aspects related to the use of segmentation techniques that are used in combination post image acquisition. Taking into account the advantages of MRI in diagnostic imaging, the survey is meant to formulate the process for MRI-based segmentation of brain tumours. The process lays emphasis on the use of wholly automated methods as we showed in Figure 2, Brain tumour in the T1 against T2 and Flair modalities.

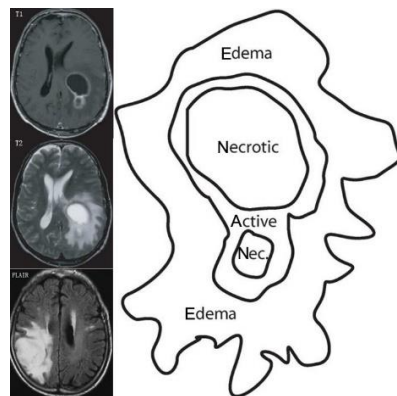


Figure 2. Brain tumour in the T1 against T2 and Flair modalities

By specifying that the segmentation models for brain tumours are divided into three primary categories, it depends on the level of human intervention required [11]. The categories are manual, fully automatic, and semi-automatic segmentation. The subsequent parts contain details about each category, which have been obtained using analysis of the specific category.

2.1. Manual segmentation

In the case of manual segmentation of brain tumours, the tumour boundaries should be defined by drawing or through the use of painting the regions with anatomical structures using specific labels. Manual segmentation uses the data in the image, along with the expertise and knowledge specific to anatomy.

Manual demarcation of tumours requires software with a sophisticated graphical user interface to facilitate drawing the areas of interest in combination with the images on display. Detecting and marking the tumour as the region of interest is the primary aspect of detection and is a computationally intensive task. MRI scanners capture 2D slices; therefore, there is a need for a human to identify the most viable image considering the clarity and the relevance of the recorded areas [4]. Pointed that manual segmentation of the brain is performed when there is a single image. Contrast injection may be used during manual segmentation to highlight regions of interest, which help in demarcating the regions. In case the individual performing segmentation is not competent with brain anatomy, [10] highlights that the process may lead to mediocre segmentation results. Marking tumour regions using slices may restrict the view for manual demarcation because of blurred images. This may cause a stripping effect during image segmentation [12].

2.2. *Semiautomatic segmentation*

Human observation is necessary during semi-automatic segmentation, especially during initialisation. Human intervention is required to validate the accuracy of the results generated. The professional may also manually correct any variance if detected. A large chunk of the current research suggests semi-automatic segmentation for brain tumours with the intent of limiting expert intervention or inputs required during the process. suggest that several essential aspects must be considered during the interactive segmentation of brain tumours, which are the computational, the interactive, and the user interface aspects [4]. The computational part uses algorithms to create a demarcation of the tumour using the parameter data.

The interactive aspect comprises human mediation on the data produced by the computer. The process leads to the creation of a translation technique crafted using the incorporation of the computational inputs as visual feedback provided to the operator, while the inputs provided by the operator are converted to parameters that may be used by the software. The input and output devices, along with the user interface, determine the interaction between a human and the computer, the user keys in the analysis of the visual information displayed on the screen. User input acts as feedback for the algorithms, which then modifies the computational process to incorporate the feedback. With respect to tumour classification, the process comprises four primary aspects, which are initialisation, intervention or feedback, and evaluation.

2.3. *Automatic Segmentation*

Such methods consist of processes where the computer completely controls the tumour segmentation process. There is an attempt to mimic human intelligence, which consists of producing deformable models using the knowledge of algorithms, modelling techniques, and computing power. Deformable models and fuzzy logic are classified as soft computing techniques. In the domain of segmentation of brain tumours, the use of pattern recognition and machine learning is critical to identifying problems for which solutions may be found by increasing human intervention in the process. Nevertheless, the creation of a program with a high degree of automation is challenging since humans make decisions using advanced domain knowledge and sophisticated visual processing, both of which are crucial to automate the process; therefore, formulating highly automated methods is complex. This applies to pattern recognition too.

2.4. *Segmentation methods*

Detection is a crucial process adopted with relation to oncology and clinical medicine. The pre-mature analysis and localisation of diseases, together with precise disease stage detection, may affect the identification of variations related to patient management which is considered instrumental in providing helpful health outcomes. Providing precise detection of the regional physiology is still dependent on precise segmentation or delineation of the tumour structure relating to the identified area of interest combined with the provided pictures developed. asserts that the primary roles of the process of segmentation include (1) quantification of permit, (2) dataset reduction by placing emphasis on quantitative assessment on the extracted areas of interest, along with the (3) development of structural connections related to physiological information sampled within the areas [4], [10], [13]. The procedure has improved the processing of several techniques for brain tumour-segmentation. Still, there is an absence of a standard segmentation method necessary for providing acceptable results related to all the imaging applications. In most cases, the techniques that are adopted use specific-imaging modalities including MRI (magnetic resonance imaging). The existing segmentation methods have been classified into 4 main categories:

- Region-based
- Threshold-based
- Pixel classification
- Model-based

2.5. Region-based methods

Region-based segmentation methods analyse the pixels within a picture through the combination of form disjoint areas by merging the adjacent pixels with homogeneity attributes that develop based on a predefined likeness. These techniques can be outlined in a general manner as follows: Let X represent an image which is segmented into N areas, where each one is represented by R_i where $i = 1, 2, \dots, N$

$$\begin{aligned} X &= \bigcup_{i=1}^N R_i \\ R_i \cap R_j &= \mathbf{0} \quad \forall i, j = 1, 2, \dots, N \\ L(R_i) &= \text{TRUE} \quad \text{for } i = 1, 2, \dots, N \\ L(R_i \cup R_j) &= \text{FALSE} \quad \text{for } \forall i, j = 1, 2, \dots, N; i \neq j \end{aligned}$$

Where $L(\cdot)$ represents a logical predicate. The area growing as well as the watershed segmentation techniques develop part of region-based techniques, with most of them used in the segmentation of brain tumour. The next section describes the existent techniques together with an assessment of the existing applications related to the available literature about brain tumour segmentation.

The region-growing technique is regarded as the simplest one, which is used in the extraction of a linked region related to similar pixels from a picture [14]. The region-growing method is initiated with no less than one seed that belongs to the developed formation of interest. The adjacent seeds are assessed and the ones that meet the developing condition are adopted and included within the procedure. The similarity condition develops from the existent range of values of pixel intensity or existent attributes related to the image. The procedure incorporates automatic and manual selection processes with respect to the seeds. The process is repeated to make sure that the region stayed filled to its capacity. The growth of the area is helpful in the process of segmentation relating to the existing similar attributes combined with the creation of a connected region. impacted the adoption of a method of region growing related to the segmentation of the MRI pictures of brain tumours [15]. The method included the repetition of statistical categorisation that was necessary in segmenting the image to different tissue classes that are developed on the basis of the existing value of signal intensity. The process affected the objects of interest identification related to the categorised images with local segmentation processes (region growing and mathematic morphology).

Others have pointed out that region growing provides a feasible and productive approach because of the requirement of limited computationally intensive tasks when compared to non-region-based techniques for the segmentation of brain tumours, concerning the homogeneous regions and tissues [16], [17] .

The primary drawback of the process concerns the partial volume effect [18], which restricts the accuracy of brain segmentation using MRI images. The partial volume effect delineates the lucidity of intensity difference between the types of tissues, especially at their border. The voxel may be in an area having more than one type of tissue. incorporated the modified region growing method (MRGM), which facilitated the elimination of effects of partial volume that is crucial to determine gradient data concerning boundary detection with higher accuracy and to plug the holes after the segmentation technique has been developed [19].

By performing an analysis and using a comparison of the segmentation performed using the region grown method, and the MRGM concerning the segmentation of brain tumours is obtained by using 3D T1 MR images. The study indicated that MRGM offers more accurate information about the volumetric measurement of the tumours [16]. This accuracy can be attributed to lesser errors produced by MRGM when compared with manual segmentation.

This process caused the formulation of several approaches concerning the use of region growing as a refining step, suggested that employing the fuzzy information fusion framework in the domain of automatic segmentation of tumour cells from the brain using a chain of several MR images (T1, T2, and PD) [20].

Edge information was retained during the process by the use of anisotropic diffusion filtering. The process facilitates the use of a new technique that calculates the mean of the variance inside the curve while the inverse of the mean gradient is calculated along the curve as the parameters of the study. The model seeks to integrate aspects regarding variance and gradient. The study established that the optimal result is obtained when the sum is minimised; the result is directly related to the required threshold. During the process step comprising region growth, the threshold value increases gradually and facilitates the recognition of the coarse boundary. Lastly, the optimised model facilitates the detection of accurate segmentation using a set of boundaries [19].

2.6. Neural Networks Based Methods

These methods employ computational models based on artificial neural networks that use ‘neurons’ as processing elements, which are interconnected and use weights. The weights (coefficients) determine the multipliers of the present connections and provide for the necessary training required to determine the coefficients.

This process has exerted significant influence on the development of numerous varieties of neural networks that are employed in the segmentation of medical images and also in other applications. Some such techniques are back-propagation based learning, multilayer perceptron (MLP), SOM neural network, and Hopfield Neural Networks (HNN), which are used for segmentation [21]. The significant characteristic of neural networks is their ability to learn the segmentation process using some training process, which makes their application lucrative in image segmentation compared to other image processing areas [22].

This study is among the initial studies using the application of MLP for the segmentation of brain tumours. It comprised initial training of the neural networks provided through a known diagnostic image. The training process yielded data that was used to formulate an MLP model. In the case of adaptive systems, data from subsequent images was used as an input to create the training dataset that followed. The new data set was then used to segment the image further. Segmentation of the image dataset used iterations. A semi-automatic method was proposed where continuous user input was required. Tumour segmentation accuracy is typically measured with Jaccard’s similarity measure, as applied among areas described as tumours by medical experts. The proposed automated techniques attained a similarity index ranging from 0.6 to 0.8. MLP networks may be trained in the segmentation of brain tumours based on textural features, with use of numerous methods [23], such as contrast, sum variance, entropy, sum of entropy, difference of entropy, inverse difference moment, angular second moment, and information measures of correlation. Through MLP, supervised learning is performed by assigning labels to all anatomical designations within the image.

Fuzzy Based Methods Fuzzy logic comprises a set of mathematical rules that derive from degrees of memberships, which replace the crisp membership criteria of conventional binary logic. Applied to brain tumour segmentation, such fuzzy systems afford the development of algorithms and methods that perform tasks related to intelligent human behaviours. Applied a fuzzy logic scheme to segment and detect tumours through the extraction of features from brain MR images, which relies on human proficiency in developing fuzzy rules [24]. This model presents unsupervised learning that is fully automated. Data is extracted through use of intensity histogram analysis, with a new approach applied towards acquiring any membership function appropriate to the medical MRI data. Detection and segmentation findings acquired using this technique are of decent quality, with highest and lowest scores corresponding to 93% and 71%. Nevertheless, experiments are conducted on just two forms of brain tumours, namely meningioma and glioblastoma multiforme.

Introduced the use of fuzzy logic processing, with C-means clustering applied to MRI for brain tumour segmentation tasks. Fuzzy clusters were exploited to initiate the region-based algorithm that iteratively shifts towards the final brain tumour boundary [25] [26]. This proposed technique was experimentally trialled to determine its efficiency at processing 15 brain MR images, wherein the manual segmentation gold-standard

procedure was available for evaluation. Satisfactory results were attained, with an average value for Jaccard coefficient of 83.19% and average sensitivity of 96.37%. An FCM clustering algorithm was utilised to segment Glioblastoma-Multiform (GBM) brain tumour forms [19]. Intensity overlapping of tissue, noise, and initialisation values led to inaccuracies in the segmentation of brain tumours. Nevertheless, the FCM algorithm was shown to be straightforward, fast, and unsupervised in application [27].

Introduced an FCM approach that used the curve-let transform to eliminate noise. Detailed descriptions of the process applied in FCM were provided without any results on the segmentation, qualitative performance, and efficiency of the model in terms of tumour detection.

2.6.1. Threshold-based methods

Thresholding refers to an efficient region segmentation technique that develops a categorisation model for the image objects by developing a comparison between fixed intensities with 1 or more thresholds for intensity, which may be local or global. When the object can be detached from the image background by integrating one threshold, it is called global thresholding. Nonetheless, when the image includes 2 or more areas related to the various objects, the process of segmentation may be started by using local thresholding. This process may cause segmentation of the image by applying many individual thresholds or through a multi-thresholding method.

Global thresholding

Intensity is regarded as the simplest attribute that may be common among pixels in a particular region. Thus, thresholding recognises a natural way, which may be used in separating light and dark regions. Thresholding involves construction of binary images from ones with grey-level by varying all the pixels below certain threshold to 0 along with all the pixels which are above the threshold to 1.

If $g(x, y)$ is a threshold version of $f(x, y)$ at some global threshold T

$$g(x, y) = \begin{cases} 1 & \text{if } f(x, y) \geq \rho \\ 0 & \text{otherwise} \end{cases}$$

Furthermore, the existence of shadows of objects in the image presents a shortcoming related to the area they fall in an object along with the included regions related to a dark object in a light backdrop. Also, the thresholding procedure may experience many changes attributed to the intensity level relating to the inhomogeneity across the area [28].

Local Thresholding

Contrary to global thresholding, there are different thresholding techniques that may be referred to as local thresholding. The developed methods may be feasible in the event that the procedure remains unable to efficiently determine a thresholding value using a histogram for the whole image or in case one threshold may be not able to provide the expected segmentation results. Identification of local threshold can be by estimating a threshold value related to different areas from the intensity histogram [29].

2.6.2. Combined Techniques

Hybrid system is a blend of various techniques of machine learning algorithms. This was developed to acquire a better combined solution in place of a single approach to the same set of problems [30]. Introduced a supervised hybrid fuzzy Bayesian clustering-based brain tumour detection system, which maps fuzzy inputs to crisp outputs during the training phase of the Bayesian system [25]. The hybrid architecture of the Bayesian scheme applied the Fuzzy and Learning Back Propagation Algorithm (FLBPA). Such results were achieved with these supervised hybrid methods are promising. Nevertheless, it is difficult to determine

generalised efficiency with the approach because of the unevenness of image pixel intensities among diverse MRI scanner features, MRI modalities, and the effects of noise. Conducted a comparative review of KNN, SVM, PNN, ISNN and Gabor Transform applications in terms of brain tumour segmentation processing. It was proposed that with light abnormalities, the highest segmentation performance may be attained by utilising SVM, whereas k-NN remains decent for darker abnormalities [30]. The study recommended that we conclude that SVM should be used for efficient segmentation of cerebrospinal fluid and skull tissue, ISNN should be employed for gray matter whereas, PNN and ISNN should be considered for better segmentation of white matter.

A Neural Network (NN) approach with DWT features is introduced for acquiring brain MRI segmentation. They used discrete wavelet transform that decomposes the images and textural features were extracted from gray-level cooccurrence matrix (GLCM) followed by morphological operation. Probabilistic neural network (PNN) classifier is used for the classification of tumours from brain MRI images [31]. From the observation results, it can be clearly expressed that the detection of brain tumour is fast and accurate when compared to the manual detection carried out by clinical experts. The performance factors evaluated also shows that it gives better outcome by improving PSNR and MSE parameters.

Combined K-means clustering together with DWT methods for medical MR image segmentation. The DWT of MR images was used to construct the neurons according to the frequency of wavelet at each grey level. Independency in the number of neurons for image size led to precise segmentation of regular axial brain MR images [32].

3. Conclusion

Proper diagnosis of brain tumours in patients requires appropriate segmentation techniques in processing brain MR images so as to deliver adequate treatment. Currently, many images from various slice orientations are deployed for mining the information needed for planning, diagnosis, and treatment. The scale of the information entails computation processing to expedite diagnosis and treatment processes. Since pace of the computation process is not an issue anymore, the key emphasis is focused on enhancing the process to mine information from the images attained through slice orientation as well as the procedure of segmentation to obtain a precise image of the brain tumour. This paper includes a discussion on certain significant and recent investigations in brain tumour detection and segmentation. The development of automated procedures for brain tumour detection and segmentation from medical MR images remains a very active research area, with many researchers involved in the field. To the best of our current knowledge, no clinically-accepted automated technique has been reported that detects and segments tumours from brain MR images.

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