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Brain MRI Image Classification for Cancer Detection Using Deep Wavelet Auto Encoder-Based Deep Neural Network

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ABSTRACT:

Brain lesion Segmentation and classification, are an integral of both computational intelligence and pattern recognition. In this process efficient algorithm was implemented in segmentation of lesion, is carried out and its features such as LBP combined with the GLCM to extract the data from the image. In this process we have proposed the semi and fully automatic methods for detection and segmentation of brain tumor. In this article, the different techniques available for segmentation have been presented. This article focuses on the work done by main segmentation a Morphological Based fuzzy C-means clustering algorithm (MFCM) is proposed for clustering. Then this process involved here in medical field to detect brain lesion and its features classification method using CNN helps to classify the severity of the Brain input.

Key words: Neural network (NN), deep neural network (DNN), auto encoder (AE), image classification.

INTRODUCTION:

Tumor is an uncontrolled growth of many cells in any part of the body .Tumors is of different types and has different characteristics and different treatments [2]. At present, brain tumors are classified as primary brain tumors and metastatic brain tumors. The former begin in the brain and tend to stay in the brain, the latter begin as a cancer elsewhere in the body and spreading to the brain. Brain tumor segmentation is one of the crucial procedures in surgical and treatment planning. Brain tumor segmentation using MRI has been an intense research area. Brain tumors can have various sizes and shapes and may appear at different locations’. Varying intensity of tumors in brain magnetic resonance images (MRI) makes the automatic segmentation of tumors extremely challenging [5]. There are various intensity based techniques which have been proposed to segment tumors on magnetic resonance images. Texture is one of most popular feature for image classification and retrieval. From the MRI Images of brain, the optimal texture features of brain tumor are extracted by utilizing FCM and JAYA algorithm process [6].

Then using these methods, such an algorithm classifies the tumor and non-tumor tissues and tumor is segmented. This method provides more efficient brain tumor segmentation compared to the segmentation technique based on existing Procedure and will provide more accurate result. Tumor is the abnormal growth of the tissues. . A brain tumor is a mass of unnecessary cells growing in the brain or central spine canal. Today, tools and methods to analyze tumors and their behavior are becoming more prevalent. Clearly, efforts over the past century have yielded real advances. However, we have also come to realize that gains in survival must be enhanced by better diagnosis tools[6]. Although we have yet to cure brain tumors', clear steps forward have been taken toward reaching this ultimate goal, more and more researchers have incorporated measures into clinical trials each advance injects hope to the team of caregivers and more importantly, to those who live with this diagnosis.

Magnetic Resonance Imaging (MRI) has become a widely-used method of high-quality medical imaging, especially in brain imaging where MRI's soft tissue contrast and non-invasiveness are clear advantages. An important use of MRI data is tracking the size of brain tumor as it responds treatment [4]. Therefore, an automatic and reliable method for segmenting tumor would be a useful tool. MRI provides a digital representation of tissue characteristics that can be obtained in any tissue plane. The images produced by an MRI scanner are best described as slices through the brain. MRI has the added advantage of being able to produce images which slice through the brain in both horizontal and vertical planes. This makes the MRI-scan images an ideal source for detecting, identifying and classifying the right infected regions of the brain. Most of the current conventional diagnosis techniques are based on human experience in interpreting the MRI-scan for judgment; certainly this increases the possibility to false detection and identification of the brain tumor [9]. On the other hand, applying digital image processing ensures the quick and precise detection of the tumor. One of the most effective techniques to extract information from complex medical images that has wide application in medical fields the segmentation process [7].

The main objective of the image segmentation is to partition an image into mutually exclusive and exhausted regions such that each region of interest is spatially contiguous and the pixels within the region are homogenous with respect to a predefined criterion. The cause of most cases is unknown. Risk factors that may occasionally be involved include: a number of genetic syndrome such as neurofibromatosis as well as exposure to the chemical vinyl chloride, Epstein-Barr virus, and ionizing radiation [11].

Magnetic resonance imaging (MRI) is the prime technique to diagnose brain tumors and monitor their treatment. Different MRI modalities of each patient are acquired and these images are interpreted by computer-based image analysis methods in order to handle the complexity as well as constraints on time and objectiveness. In this thesis, two major novel approaches for analyzing tumor-bearing brain images in an automatic way are presented: Multi-modal tissue classification with integrated regularization can segment healthy and pathologic brain tissues' including their sub-compartments to provide quantitative volumetric information [1]. The method has been evaluated with good results on a large number of clinical and synthetic images [8]. The fast run-time of the algorithm allows for an easy integration into the clinical work flow.

An extension has been proposed for integrated segmentation of longitudinal Patient studies, which has been assessed on a small dataset from a multi-center clinical trial with promising results. Atlas-based segmentation with integrated tumor-growth modeling has been shown to be a suitable means for segmenting the healthy brain structures surrounding the tumor. Tumor- growth modeling offers a way to cope with the missing tumor prior in the atlas during registration. To this end, two different tumor-growth models have been compared [12]. While a simplistic tumor growth model offered advantages in computation speed, a more sophisticated multi-scale tumor growth model showed better potential to provide a more realistic and meaningful prior for atlas-based segmentation. Both approaches have been combined into a 10generic framework for analyzing tumor-bearing brain images, which makes use of all the image information generally available in clinics. This segmentation frame work paves the way for better diagnosis, treatment planning and monitoring in radio therapy and neurosurgery of brain tumors.

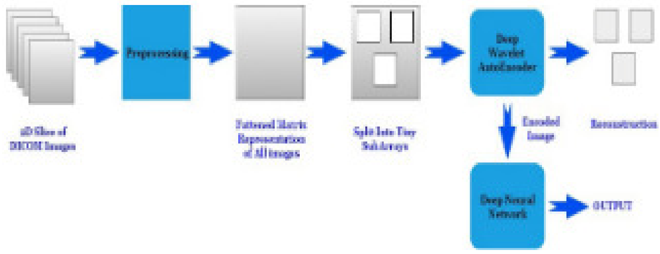
LITERATURE SURVEY:

Image segmentation is one of the crucial task in the field of machine learning and is alleged to be one of the critical application in the clinical area. Many researchers have done extensive research in the field of image segmentation and analysis. Despotovic et al. [4] provided an extensive review on the various segmentation techniques that are used for brain analysis in medical image or brain image. They highlighted differences between various segmentation techniques, steps related to preprocessing of MRI images, etc. Allaouni and Mohammed [1] proposed a segmentation method based on evolutionary algorithms and region growing. The suggested technique was carried out and was validated on around 1000 synthetic images based on approximately6 criteria of valuation.

Hiralal and Menon [6] also provided a detailed overview about the various brain image segmentation methodologies of brain MRI images. They highlighted a very clear discussion for the selection of appropriate segmentation method for MRI brain images for the purpose of analysis and prognostication. Yazdani et al. [12] presented a bird's overview about the brain image segmentation methodologies, keeping intensity in homogeneity, noise and partial volume, etc. into considerations. In the work, they divided the problem into five different groups based on their workflow process and segmentation principles. Xiao and Tong [11]designed an image segmentation algorithm based on Fuzzy C-Means (FCM) algorithm and Support Vector Machine (SVM) algorithm. They merged the above two algorithms and proposed a segmentation technique that was tested to be beneficial to the high noise and high bias field in a brain image Another extensive survey was made by Nayak et al They combined fuzzy clustering and Markov random field and integrated the fuzzy clustering membership of the original image into Markov random field function. This merging acted as a segmentation supporting information and the proposed method achieved higher efficiency. Jose et al. [7] suggested a technique where the fuzzy c-means and k-means algorithm we recombined together and for the brain tumor detection and detecting the area of tumor spread using brain MRI images. The method worked fine except with a limitation where determining fuzzy membership was hard and intense.

Ganesh and Palanisamy [5] used and proposed multiple kernel fuzzy C-means clustering algorithm for MRI images fuzzy segmentation. The proposed method aimed at refining the classification accuracy by lessening the number of iterations and is quite effective the noise factor. Sheen et al. [9] proposed a MRI fuzzy segmentation with neural network optimization for brain tumor detection. It used the neighborhood attraction with the above optimization technique to help in the accurate detection of brain tumor from the images. Shalini et al.[8]suggested method where the weighted fuzzy was used to segment the brain tumor from the given images and the kernel metric was used to increase the segmentation performance. It provided a high efficiency and accuracy as compared to any other prevailing method in this domain. An effective neural network based brain tumor detection technique was proposed by Damodharan and Raghavan [3] which focused on brain tissue segmentation. The proposed method provided a desired efficiency and accuracy in relevance to brain tissue and tumor segmentation, feature extraction and classification and etc.

A Wavelet-like Auto Encoder (WAE) using neural network was proposed by Chen et al. [2] that decomposes the original image into low resolution images for the purpose of classification. These low resolution channels or images are further used as an input to the Convolution Neural Network (CNN) for reduction of computational complexity without altering the accuracy factor. Vincent et al. [10] established a stack demising auto encoder by using a demising criterion for learning needed representation of a deep learning network.



4. METHODOLOGY:

4.1 EXISTING SYSTEM:

The existing system describes a novel algorithm for interactive multi label segmentation of N-dimensional images. Given a small number of user-labeled pixels, the rest of the image is segmented automatically by a Cellular Automaton. The process is iterative, as the automaton labels the image, user can observe the segmentation evolution and guide the algorithm with human input where the segmentation is difficult to compute .In the areas, where the segmentation is reliably computed automatically no additional user effort is required. Results of segmenting generic photos and medical images are presented. Our experiments show that modest user effort is required for segmentation of moderately hard images. The existing system takes an intuitive user interaction scheme - user specifies certain image pixels (we will call them seed pixels) that belong to objects that should be segmented from each other. The task is to assign labels to all other image pixels automatically, preferably achieving the segmentation result the user is expecting to get.

The task statement and input data is similar to and, however the segmentation instrument differs. Our method uses cellular automaton for solving pixel labeling task. The method is iterative, giving feedback to the user while the segmentation is computed. Proposed method allows (but not requires) human input during labeling process, to provide dynamic interaction and feedback between the user and the algorithm. This allows to correcting and guidance of the algorithm with user input in the areas where the segmentation is difficult to compute yet does not require additional user effort where the segmentation is reliably computed automatically. One important difference from the methods based on graph cuts is that seeds do not necessarily specify hard segmentation constraints. In other words-user brush strokes need not to specify only the areas of firm for ground or firm background, but instead can adjust the pixels state continuously, making them 'more foreground' or 'a little more background' for example. This gives more versatile control of the segmentation from the user part and makes the process tolerable to inaccurate paint strokes.

As we have already emphasized in the introduction, our hope is to stir up the research community, motivating to search new ideas in the field of cellular automata and evolution any computation and applying them to interactive image segmentation. We expect that results exceeding our current can be obtained. However, our current method can already compete with elegant achievements of graph theory. In this section we will try to compare current top performing methods with ours and point out advantages and disadvantages of our scheme. We take four methods – Graph Cuts, Grab Cut, Random Walker and Grow Cut and compare them by several criteria: segmentation quality, speed and convenience for the user. Accurately speaking, the methods differ seriously by the amount of information that they extract from the image. Grab Cut uses most information - it computes the evolving color statistics of fore ground and background and takes into account color difference between neighboring pixels. Graph Cuts differs in using color statistics collected from the user-specified seeds only, computed before the segmentation start.

Random Walker uses only intensity difference between neigh boring pixels. Our current Grow Cut variant also does not take advantage of object color statistics; however it can be easily extended to maintain regions color statistics and use them in automaton evolution. The performance of described photo editing methods was evaluated in (except for the intelligent paint). The authors have clearly shown, that methods based on graph cuts allow achieving better segmentation results with less user effort required, compared with other methods. One of the few drawbacks of the graph-based methods is that they are not easily extended to multi-label task and the other is that they are not very flexible - the only tunable parameters are the graph weighting and cost function coefficients. For example, additional restrictions on the object boundary smoothness or soft user-specified segmentation constraint scan not be added readily.

As for the intelligent paint, judging by the examples supplied by the authors, the advantage of their method over the traditional 'magic wand' is in speed and number of user interactions. As it appears from the algorithm description and presented results, it is unlikely that intelligent paint would be capable of solving hard segmentation problems. Precise object boundary estimation is also questionable, because the finest segmentation level is obtained by initial tobogganing over segmentation, which may not coincide with actual object borders. Speaking about medical images, the best performing method is random walker (judging by the provided examples). It leaves behind both watershed segmentation and region growing behind in quality and robustness of segmentation. The quality of segmentation comparable to is graph cuts, but random walker is capable of finding the solution for number of labels However, it is rather slow and its implementation is not an easy task. Also, methodic tension to achieve some special algorithm properties (i.e. controllable boundary smoothness) is not straightforward. It should be mentioned, that multi-labeling task scan be solved by min-cut graph algorithms, but no attempt to apply this multi-labeling method to interactive image segmentation is known to us. The process is iterative, as the automaton labels the image, user can observe the segmentation evolution and guide the algorithm with human input where the segmentation is difficult to compute.

DISADVANTAGES:

- This method was limited to enhancing tumors with clear enhancing edges.
- The other is that they are not very flexible.
- This method was limited to enhancing tumors with clear enhancing edges.

4.2 PROPOSED SYSTEM:

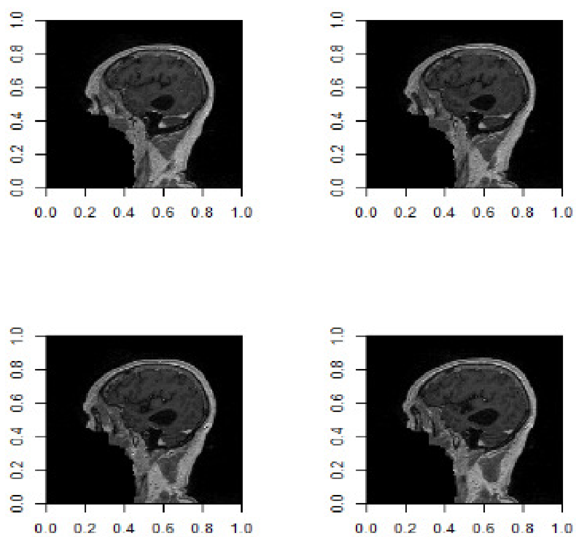
Brain MRI plays a very important role for detection of brain tumor patients. The medical image by the radiologist is a time consuming process and also the accuracy depends upon their experience. Thus, the computer aided systems becomes very necessary as they overcome these limitations. Several automated methods are available, but automating this process is very difficult because of different appearance of the tumor among the different patients. There are various feature extraction and classification methods which are used for detection of brain tumor from MRI images. In this process, we proposed the algorithm like k – means clustering and then the GLCM Performs good segmentation and feature extraction. The fine segmentation is achieved by this method and then the feature extraction performs the feature stability to the image.

ADVANTAGES:

- This algorithm can correctly separate the regions that have the same properties we define.
- This methods can provide the original images which have clear edges the good segmentation results

5. RESULTS AND DISCUSSION:

The performance comparison between proposed DWA-DNN model and other traditional classification techniques. The performance has been measured with four parameters those are Accuracy, Specificity, Sensitivity and F-Score. From the table 3, it has been experimentally proved that DWA-DNN technique outperforms compared to other outperforms compared to other



Techniques	Parameters	Values
Auto encoder	No of layers No of encoded units Units types Lambda (weight decay parameter) Beta (weight of sparsity penalty term) Rho (sparsity parameter) Epsilon(parameter for initializing weights) Optimization method Maximum iteration	5 64*64 Logistics 0.002 6 0.01 0.001 BFGS Algorithm 2000
Deep Neural Network	Activation function Learning rate Momentum No. of epochs Batch size	Sigmoid 0.8 0.5 1000 100

Traditional non-deep learning techniques. It can be clearly seen that the DWA-DNN technique have an overtly good accuracy when compared to TDNN or PNN algorithm and also the specificity, sensitivity and F-score measure is quite good as compared to the previous two. Further a comparison has been made between DNN; Auto encoder based DNN and proposed DWA-DNN technique. All experiments have been carried out using a 10-fold cross validation.

A.STATISTICAL ANALYSIS:

McNamara's statistical test to compare the performances of DNN vs DWA-DNN and AE-DNN vs DWA-DNN performances. The McNamara's test, which is based upon the

TABLE2. Performances comparison between deep learning vs,non deep learning based approaches.

Classification Techniques	Accuracy	Specificity	Sensitivity	F-score
MLPNN	0.85+0.33	0.83+0.26	0.87+0.22	0.84+0.30
RBFNN	0.67+0.22	0.75+0.23	0.74+0.34	0.74+0.21
ELM	0.90+0.15	0.87+0.32	0.91+0.22	0.89+0.25
PNN	0.89+0.18	0.90+0.28	0.87+0.29	0.88+0.32
TDNN	0.86+0.32	0.85+0.25	0.88+0.23	0.86+0.29
DWA-DNN	0.93+0.14	0.92+0.16	0.94+0.26	0.93+0.15

TABLE3. Performances comparison between traditional DNN,AE-DNN and proposed DWA-DNN.

Classification Techniques	Accuracy	Specificity	Sensitivity	F-score
DNN	0.89+0.18	0.88+0.26	0.91+0.19	0.90+ 0.22
AE-DBN	0.90+0.19	0.89+0.24	0.91+0.18	0.90+ 0.23
DWA-DNN	0.93+0.14	0.92+0.16	0.94+0.26	0.93+ 0.15

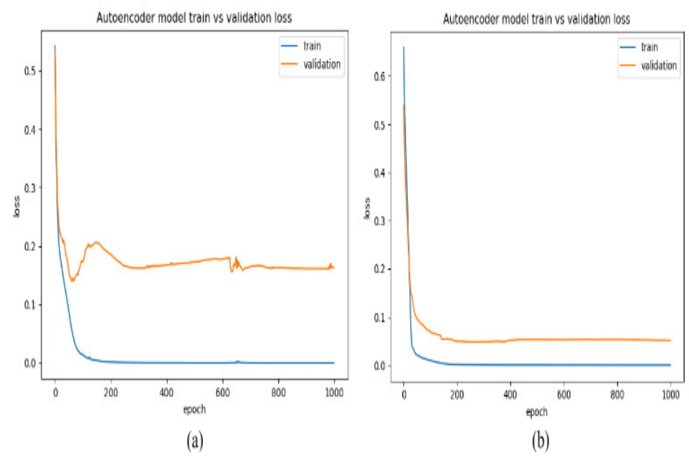


Figure1 .Loss graph for Auto encoder model. (a) Simple AE model. (b) Wavelet AE model.

Standardized normal test statistic, is used to demonstrate whether the two methods perform differently in the statistical sense. The statistic is computed as shown in eq.(5).

$$MNij = \frac{mnij - mnji}{\sqrt{mnij + mnji}} \quad (5)$$

Where, mnij denotes number of samples misclassified by i classifier but not by j classifier. Similarly mnji denotes number of samples misclassified by j classifier but not by classifier. This is basically derived from the chi-squared distribution shown in eq.(6):

$$\chi 2 = \frac{(b - c)2}{b + c} \quad (6)$$

Under the null hypothesis mnij is equal to mnji. That is equivalent to the number of counts for

$$mnij = mnji = (mnij + mnji)/2 \quad (7)$$

Classification Techniques	Overall accuracy	Average accuracy	Kappa statistics
DNN	91%	89%	0.4811
AE-DNN	93%	91%	0.5732
DWA-DNN	96%	93%	0.6522

TABLE4. Measure of classification techniques

At 95% level of confidence, the difference of accuracies between the two methods (DNN and DWA-DNN) is significant as |MNij| = 3.841 which is greater than 1.96. Hence, the null hypothesis can be rejected. Similarly, at 95% level of confidence the difference of accuracies between the two methods (AE-DNN and DWA-DNN) is significant as |MNij| = 2.147 which is greater than 1.96. Hence, the null hypothesis can be rejected and the alternative hypothesis can be accepted that states there is a significant difference between the corresponding two different classifiers.

Measuring the overall accuracies (OAs), average accuracies (AAs), and Kappa statistics (Kappa) of ten runs of trainings and tests of DNN, AE-DNN and DWA-DNN is presented below in table 4.

6. CONCLUSION AND FUTURE WORK:

Interpretation of medical image dataset has always been a time consuming process and handling them is itself a challenge. In this paper, the solutions dealt made us to think in the perspective of DNN, AE and wavelet transformation. The proposed DWA-DNN classifier have achieved a great result in terms of accuracy, specificity, sensitivity and other performance measure when compared the existing classifiers like DNN, AE etc. The result of the proposed DWA-DNN technique shows that its accuracy and the statistical measure is far more competing than any other non-deep learning techniques. It would be far more interesting to explore the possibility of combining the DNN with many other variation of the auto encoder to see the effect or performance in the same brain MRI dataset.

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