

BRAIN TUMOR DETECTION USING ANN WITH MULTILEVEL ROI-BASED FEATURES

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ABSTRACT: The Indian economic system relies heavily on productivity in farming, and disease detection is crucial for sustainable agriculture. Monitoring crops and identifying diseases requires extensive knowledge and processing time. Machine Learning algorithms can help predict increased agricultural yields, addressing a significant challenge in the industry. Automated or semiautomated techniques are required to attain this level of precision. This study presents an automated segmentation technique based on multilayer ROI-based features using Artificial Neural Networks (ANNs). To be more precise, pictures are processed using the Brain Lab software, which is then used to assess the gray matter volume, cortical thickness, and cortex surface area at each ROI. The experimental outcome shows that the classification is significantly improved by our multilayer ROI-based feature technique. Therefore, designing and applying multilayer ROI-based feature-based brain tumor detection using artificial neural networks (ANNs) yields improved outcomes in terms of efficiency, accuracy, and precision.

KEYWORDS: Magnetic resonance imaging, Multilevel ROI-based features, brain tumor, Artificial Neural Network (ANN)

I. INTRODUCTION

The fundamental structural unit of all living organisms is the cell. Human body contains about 100 trillion cells and each of them has its own functions. These cells have to divide and should form new cells in a controllable way. Then only the body can function correctly. But there are cases in which the cells divide and grow without any control so that a huge amount of

unwanted tissue will be formed. It is known as tumor. Tumors can occur in any parts of the body.

Brain tumor can be considered as one of the serious and life threatening tumors. The brain tumor is the abnormal growth of cells or tissues in the brain. The tumor in any part of the body can spread to brain. Tumor shaves the capability to destroy all the brain cells [1].

According to the World Cancer Research Fund, in 2018 there were 18 million cancer cases around the world. Among them new cases of brain tumors were about 2,96,851 which was 1.7% of all cancers. Brain tumors are expansile lesions that originate in the brain [2]. They can be divided into benign (non-cancerous) and malignant (cancerous) according to their aggressiveness, and classified into four grades using the WHO classification for Central Nervous System (CNS) tumors ranging from 1 to 4, according to their malignancy. Non-cancerous tumors rarely spread to healthy surrounding cells, examples are meningiomas and pituitary tumors, often of lower grades.

Malignant brain tumors infiltrate the surrounding parenchyma with variable aggressiveness. Glioblastoma (GBM) is the most common and aggressive type of malignant brain tumor, commonly classified as a grade 4 CNS tumor with dismal survival. Brain tumors can also be categorized according to their origin into

primary and secondary brain tumors, with the former originating in the brain and the latter usually in a distant site. The most usual tumor types are glioma, meningioma and pituitary. Glial cells are the place from where glioma tumor arises. Meningioma tumor grows from dura mater and the originating place of pituitary tumor is pituitary gland [3].

Most of the meningioma and pituitary tumors are non-cancerous but most cases, glioma tumors are often cancerous type. It is much essential to find out to save the life of patients without wasting time. Brain images consist of high complication in that fact hardly expert physicians can analyze tumors. So, detection of brain tumor using image processing is a strenuous task in medical sector [4]. Digital image processing is effective utensil and easy way to point out and explore brain tumors effortlessly.

In this context, brain tumor classification and segmentation have become pivotal for image analysis. Brain tumor classification can be performed with different methods, including manual classification and computer-aided classification. Manual classification of brain tumors is very time-consuming and prone to error. However, manual classification cannot be ignored, as it is still the reference standard both for clinical care and used as a comparison for other techniques.

Brain tumors are graded as slow-growing or aggressive. A benign (slow-growing) tumor does not invade the neighboring tissues; in contrast, a malignant (aggressive) tumor propagates itself from an initial site to a secondary site [5]. According to WHO, a brain tumor is categorized into grades I–IV. Grades I and II tumors are considered as slow-growing, whereas grades III and IV tumors are more aggressive, and have a poorer prognosis. In this regard, the detail of brain tumor grades is as follows. Grade I: These tumors grow

slowly and do not spread rapidly. These are associated with better odds for long-term survival and can be removed almost completely by surgery. An example of such a tumor is grade I pilocyticastrocytoma. Grade II: These tumors also grow slowly but can spread to neighboring tissues and become higher grade tumors. These tumors can even come back after surgery. Oligodendroglioma is a case of such a tumor. Grade III: These tumors develop at a faster rate than grade II, and can invade the neighboring tissues. Surgery alone is insufficient for such tumors, and post-surgical radiotherapy or chemotherapy is recommended [6]. An example of such a tumor is anaplastic astrocytoma. Grade IV: These tumors are the most aggressive and are highly spreadable. They may even use blood vessels for rapid growth. Glioblastoma multiforme is such a type of tumor.

An successful surgery of medical treatment require specific information about edge of the tumor; A neural network is a powerful computational data model that is able to capture and represent complex input/output relationships. And also it is provides powerful tool to help doctors to analyze, model and make sense of complex clinical data across a broad range of medical image applications. Most applications of ANNs in medicine are classification problems such as pattern recognition; that is, the task is on the basis of the measured features to assign the patient to one of a small set of classes. In this project they used back propagation network which one of Artificial neural networks types. After they create the network the training processing come by transfer functions which calculate a layer's output from its net input by using training Algorithm.

II. LITERATURE SURVEY

Palash Ghosal, Lokesh Nandanwar, Swati Kanchan, Ashok Bhadra, Jayasree

Chakraborty, Debashis Nandi, et. al., [7] presented MRI tumor classification techniques using CNN. ROI based segmentation, zero centering of intensity, normalization and rotation are the preprocessing steps. 93.83% overall accuracy was found. Different clustering algorithms and classification techniques were implemented for the improvement of accuracy. This research is worked with artificial neural network because of paramount advantages. ANN is less complex, easier method.

Mustafa R. Ismael, Ikhlal Abdel-Qader. et al., [8] introduced a CAD system to classify 3 types of tumors using back-propagation neural network. Segmentation was done by ROI. Both DWT and Gabor filter were applied for feature extraction process. Total ten types of features were extracted from segmented images. 120 features were extracted DWT and 150 features were extracted from Gabor filters. Total 270 features worked for classification process. Obtained accuracy was 91.9 % of this method.

Zhenyu Tang, Ahmad Sahar, Yap Pew-Thian, Shen Dinggang et.al, [9] presents a new framework of MAS (Multi-atlas segmentation) for MR tumor brain images. MAS basically works by registering and fusing label information from numerous normal brain atlases into a new brain image for the process of segmentation. Mostly it is framed for normal brain images, though the tumor brain images remains a challenging concern for it. For resolving this concern, at the initial level of MAS framework, a new low-rank method is being adopted for retrieving the recovered image of normal brain from the MR tumor brain image relying upon the normal brain atlas information. In the next step, normal brain atlases are being registered for recovering the image without being affected by tumors

C.Hemasundara Rao, Dr. P.V. Naganjaneyulu, Dr.K.Satya Prasad et.al, [10] presents an automated method for detecting and segmenting affected the brain tumor areas. There are three stages: 1. initial segmentation 2. Modeling of energy functions and 3. Optimizing the energy function. To achieve reliable segmentation, the information present in T1 and FLAIR MRI images are being utilized. CRF (Conditional Random Field) based framework is employed to merge the information existing in T1 and FLAIR in probabilistic region.

Sergio Pereira et.al [11] presents automated methods for brain tumors identifying and type cataloging by utilizing MRI images of brain right from the initial time when one could attempt to scan and freight medical images in the computer system. On the contrary, NN (Neural Networks) and SVM (Support Vector Machine) being the commonly adopted methods. As NN offer better performance.

Garima Singh, Dr. M.A. Ansari et.al, [12] presents the idea of soft thresholding DWT for improvisation and genetic algorithms for the purpose of image segmentation. It's revealed that such algorithms can be implemented for grey-level magnetic resonance images. The proposed approach utilizes the potential of GA for resolving optimization issues with a large search space (which represents label of every single image pixel). Also, the proposed method integrates any prior available knowledge (like the local ground truth). The established method obtained SNR value ranging from (20 to 44) and segmentation accuracy from (82% to 97%) related to detected tumor pixels on the basis of ground truth.

D. Merkitich, G. Stebbin, B. Bernard, and J. Goldman, et.al [13] investigate relationships of gray matter atrophy on structural magnetic resonance imaging (MRI) to cognitive domains in Parkinson's

Disease (PD). Background: Cognitive dysfunction is a frequent and debilitating consequence of PD. Detecting neuroanatomical correlates of different aspects of cognitive functioning on brain MRI may provide biomarkers that can predict cognitive decline in PD. Methods: 101 PD subjects underwent clinical/neuropsychological evaluations, T1-weighted MRI brain sequences, and cognitive classification by Movement Disorder Society criteria (cognitively normal, n=29; mild cognitive impairment, n=47; demented, n=25). Z-scores for the cognitive domains (attention/working memory, executive function, memory, language, visuospatial function) were calculated. Whole-brain voxel-based morphometry analyses were conducted using SPM8, covarying for age, PD duration, and scan type.

B. Peng, Z. Chen, L. Ma, and Y. Dai, et.al [14] high resolution T1-weighted MR images were obtained from eighteen T2DM and seventeen normal controls. All images were processed using our newly developed BrainLab toolbox. Declines of gray matter volume, cortical thickness, and surface area were found in T2DM patients. Significantly reduced ROIs of gray matter volume happened in subcortical gray nuclei (left caudate and right caudate), and significantly reduced ROIs of cortical thickness occurred in temporal lobe (left superior temporal gyrus), parietal lobe (left angular gyrus), and occipital lobe (right superior occipital gyrus, left middle occipital gyrus and right cuneus). Apparently reduced ROIs of surface area were mainly distributed in frontal lobe (right superior frontal gyrus (dorsal) and left paracentral lobule). The findings indicated that T2DM caused brain changes in specific regions.

G. Singh and L. Samavedham, et.al [15] describe a methodology that has the potential to be translated into first-line diagnostic tool for NDs. We also

demonstrate the applicability of this methodology for diagnosing PD subjects in early stages of the disease, i.e., subjects in age of 31–60 years.

III. Design And Implementing Of Brain Tumor Detection With Multilevel ROI-Based Features Using ANN

The block diagram for design and implementing of brain tumor detection with multilevel ROI-based features using ANN is represented in Fig.1.

The MRI image can be obtained from the patient data base on the computer when the person undergoes the MRI scanning. Usually MRI images looks like a black and white images. This is taken as input image.

The technique of Image pre-processing involves: data cleaning, data transformation, data integration, data resizing, data reduction etc. The image pre-processing eliminates unnecessary data and smooth up noisy data, detect and eliminate the outlier and rectify the data inconsistencies. Lastly, normalization and aggregation is performed. The technique of Image-processing proves to be highly significant in determining particular heart image, removing noise and for improvising the quality of the image.

Image Segmentation is a common technique of digital image processing. Lately, Brain tumor image sectioning in MRI has spurred up as a popular research in the domain of medical imaging system. The process of Segmentation.Image is employed for segmenting the images. It directly extracts features from pixel images with least pre-processing involved. The network utilized is LinkNet which being a light deep neural network architecture that's developed to carry out semantic segmentation. The LinkNet Network contains encoder and decoder blocks which basically manage to split the

image and re-build again before it's forwarded via few final convolutional layers.

The ROI-based features, including Gray Matter (GM) volume, thickness of cortex, and surface area of cortex, were extracted on the MR images based on the template for each subject that includes 78 ROIs (39 for the right hemispheres and 39 for the left hemispheres). The framework of the classification is done.

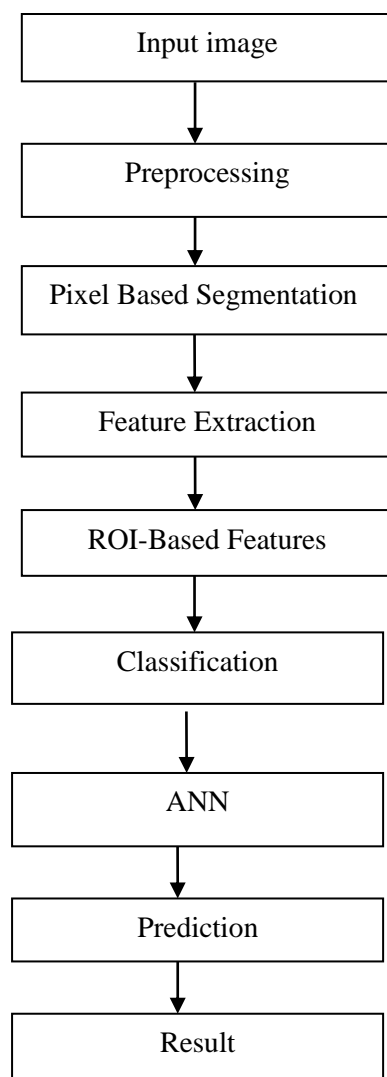


Fig.1: Block Diagram Of Design And Implementing Of Brain Tumor Detection With Multilevel ROI-Based Features Using ANN

The classification in neuroscience usually contains high dimensional features. It is challenging for the classifier with high-

dimensional features to become generalizable and fit the data appropriately, which is needed to be addressed by reducing the dimensions of the features. Feature selection is widely utilized in identification of irrelevant information for making a reduction in feature dimension and improving the capabilities for evolution of the algorithm in the future. In this method, two filter-based methods were first applied to decrease feature amount, accompanied by the wrapper-based method to further choose the appropriate features for prediction of each group. Primarily, the features with significance level under the threshold ($p < 0.05$) were reserved for following steps. After that, the other filter-based method, named minimum Redundancy and Maximum Relevance (mRMR) was employed to make a reduction of the dimension of features.

In order to evaluate the performance of classification, statistical approaches were employed to judge the property of the classification method using the assessment parameters. The entire data collection was divided randomly into two parts, one for training the samples to obtain the appropriate classifier and the other for predicting the outcome by using the ANN method.

IV. RESULT ANALYSIS

The result analysis of the described design and implementing of brain tumor detection using ANN is demonstrated in this section.

Table.1: Performance Analysis

Performance metrics	Single-level ROI-based features	Multilevel ROI-based features
Accuracy	97.3	85.5
Precision	93.4	75.3

In fig.2 the comparison graph shows that the multilevel ROI-based features using ANN technique has higher accuracy than the single-level ROI-based features.

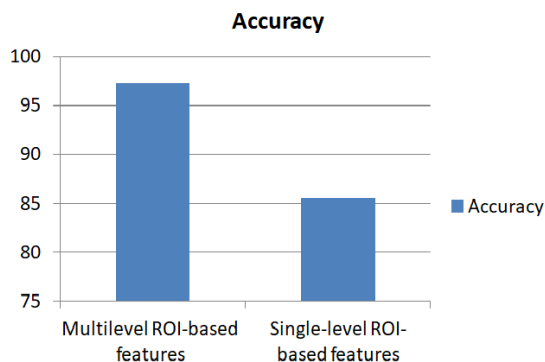


Fig.2: Accuracy Performance Comparison

The precision comparison graph is shown in fig.3. The results show higher precision value for multilevel ROI-based features using ANN technique when compared with single-level ROI-based features.

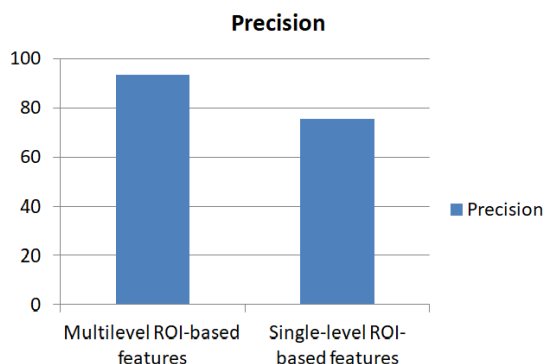


Fig.3: Precision Performance Comparison

V. CONCLUSION

In the field of medicine, brain tumor detection has proven to be a widespread cause. A brain tumor is defined as an abnormal mass of tissue in which there is no control over the cells' uncontrollable, rapid multiplication. Image segmentation is the method used to identify the aberrant tumor location in the brain. With the combination of volumetric and cortical data retrieved from the brain, the design and implementation of brain tumor detection with multilayer ROI-based features utilizing the ANN classification approach described in this method produced incredibly good performance.

This technique offers a way to identify the cerebrum's microstructural pattern changes early on. The multilevel ROI-based features perform better than the single-level ROI-based features. Specifically, promising classification results are achieved using combined multilevel ROI-based features. The experimental results achieved that the method with multilevel ROI-based features achieved significant improvement of the classification. Hence, design and implementing of brain tumor detection with multilevel ROI-based features using ANN achieved better results interms of accuracy and precision.

VI. REFERENCES

- [1] L. Wang, F. Shi, G. Li, and D. Shen, "4d segmentation of brain MR images with constrained cortical thickness variation," *PloS one*, vol. 8, no. 7, pp. e64207, Jul. 2013.
- [2] G. Wu, M. Kim, Q. Wang, and D. Shen, "Hierarchical attribute-guided symmetric diffeomorphic registration for MR brain images," in *Medical Image Computing and Computer-Assisted Intervention*, vol. 7511, pp. 90-97, 2012.
- [3] World Cancer Research Fund, *Worldwide cancer data (2019)* [online]. Available: <https://www.wcrf.org>, Accessed on: July 23, 2019J. Clerk Maxwell, *A Treatise on Electricity and Magnetism*, 3rd ed., vol. 2. Oxford: Clarendon, pp.68–73.
- [4] Hasan Ucuzal, şeyma YAŞAR, Cemil Qolak, "Classification of brain tumor types by deep learning with convolutional neural network on magnetic resonance images using a developed web based Studies and Innovative Technologies (ISMSIT), *IEEE Xplore*, 16 December 2019
- [5] J. M. Cohen, D. J. Civitello, M. D. Venesky, T. A. McMahon, and J. R. Rohr, "An interaction between climate change and infectious disease drove widespread amphibian declines," *Global change biology*, vol. 25, pp. 927-937, 2019.
- [6] Gurkarandesh Kaur, Ashish Oberoi, "Development of an Efficient Clustering Technique for Brain Tumor

Detection” , International Journal of Computer Sciences and Engineering, Vol.6(9), Sept. 2018.

[7] Palash Ghosal, Lokesh Nandanwar, Swati Kanchan, Ashok Bhadra, Jayasree Chakraborty, Debashis Nandi, “ Brain Tumor Classification Using ResNet-101 Based Squeeze and Excitation Deep Neural Network” , 2019 Second International Conference on Advanced Computational and Communication Paradigms (ICACCP), IEEE, 2528 February 2019.

[8] Mustafa R. Ismael, Ikhlas Abdel-Qader, “Brain Tumor Classification via Statistical Features and Back-Propagation Neural Network” , 2018 IEEE International Conference on Electro/Information Technology (EIT), IEEE Xplore, 22 October 2018.

[9] Zhenyu Tang, Ahmad Sahar, Yap Pew-Thian, Shen Dinggang “Multi-Atlas Segmentation of MR Tumor Brain Images Using Low-Rank Based Image Recovery”, © IEEE Trans Med Imaging, vol. 37(10), 2018, p.p. 2224–2235.

[10] C.Hemasundara Rao, Dr. P.V. Naganjaneyulu, Dr.K.Satya Prasad “Brain tumor detection and segmentation using conditional random field”, © IEEE 7th International Advance Computing Conference, 2017, p.p. 807-810.

[11] Sergio Pereira et al, “Brain Tumor Segmentation using Convolutional Neural Networks in MRI Images”, IEEE Transactions on Medical Imaging, (2016).

[12] Garima Singh, Dr. M.A. Ansari “Efficient Detection of Brain Tumor from MRIs Using K-Means Segmentation and Normalized Histogram”, © IEEE, 2016.

[13] D. Merkitch, G. Stebbin, B. Bernard, and J. Goldman, “Neuroanatomical correlates of cognitive functioning across the Parkinson's Disease cognitive spectrum,” Neurology, vol. 84, no. 14, pp. P3.006, Apr. 2015.

[14] B. Peng, Z. Chen, L. Ma, and Y. Dai, “Cerebral alterations of type 2 diabetes mellitus on MRI: A pilot study,”

Neuroscience letters, vol. 606, pp. 100-105, Oct. 2015.

[15] G. Singh and L. Samavedham, “Unsupervised learning based feature extraction for differential diagnosis of neurodegenerative diseases: a case study on early-stage diagnosis of Parkinson disease,” Journal of neuroscience methods, vol. 256, no. 30, pp. 30-40, Dec. 2015.