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A Survey on Recent Technologies used in Brain Tumor Classification and Survival Outcome Prediction

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Abstract - *Detection, and classification plays a crucial role for proper diagnosis and it helps in the treatment of brain tumor patients. Among the various imaging techniques used to detect tumors in the brain, Magnetic Resonance Imaging (MRI) stands out because of its superior image quality. There were several techniques being used from the last few decades for medical image analysis, starting from low-level pixel processing to the latest techniques like Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN). By adapting Machine Learning (ML) and pattern recognition approaches, the efficiency of classification and survival period prediction can be increased, hence reducing the burden on human judgment.*

Key Words: Magnetic Resonance Imaging, Convolutional Neural Network, Machine Learning, Random Forest, Deep Learning.

1. INTRODUCTION

A brain tumor can be quoted as abnormal and abundant growth of tissues in the brain [8]. This type of unwanted growth in the brain may affect normal functioning. The brain tumor is mainly classified into the primary tumor and metastatic tumor. A primary tumor is the one that starts to develop in the brain itself and does not spread to their surroundings, whereas metastatic tumor starts to develop somewhere in the body and later spreads to the brain. Based on the mode of spread, it can be classified into benign and malignant tumors. Benign tumors grow slowly and do not spread widely. Malignant tumors grow quickly and can spread to their surrounding. On average, over one million cases have been reported in India per year, among which the most common type of tumor is glioma, found on a large scale in adults, which constitutes 78 percent of malignant tumors. Gliomas are the most intrusive and wide-spreading tumors and regrettably, the survival period does not exceed more than two years for these patients. Hence detecting the tumors and classifying the tumors is the highest priority, which helps to determine the rate of the treatment.

Automated medical image analysis has been improved because of the possibility to scan and upload copies of images to the computer. In the field of automated medical image analysis, low-level pixel processing techniques like line and edge detection filters were being used during the 1970s to the 1990s. Whereas, more supervised techniques like segmentation and feature extraction were implemented by the end of the 1990s. The concept of recognition of patterns and machine learning is becoming very trending and stands out in the development of many successful medical systems that were used for analysis. Several imaging techniques like XRay, Computed Tomography (CT), Ultrasonography, Positron Emission Tomography (PET), and Magnetic Resonance Imaging (MRI) have helped in the field of image analysis.

Among various imaging techniques used, MRI finds greater application by making the process of image segmentation easier. MRI makes use of the radio waves and the magnetic field to develop detailed pictorial results of the organs and tissues within the body. MRI is a very powerful imaging technique that provides extremely clear and detailed images of soft-tissue structures compared to other imaging techniques. This advantage of MRI leads to efficient segmentation and classification of brain tumors.

The next logical task is making computers understand the features of MRI images which represent the data in hand as the solution for the problem. In recent days, Convolutional Neural Network (CNN) is the most efficient model in the field of image analysis. CNN is a class that is commonly applied to analyze visual imagery for classification, segmentation, object detection, and many other image processing tasks. CNN may have any number of hidden layers. Additionally, the presence of embedded layers such as fully connected layers can be very powerful in image analysis. Even though CNNs are not simple in theory, in practice, they are highly efficient. Inside the CNN architecture, convolutional filters act as feature extractors, and features like structural and required spatial information that are more complex can be extracted by going more deeper.Small filters are convolved to extract the features with the input patterns, later selection of distinct features is done. At last, the network is trained for classification.

The application of convolutional layers is that feature maps can be obtained by convolving images and kernels. These feature maps are connected using the weight of the kernel to the previous layer. Backpropagation helps the kernels to adapt the weights to enhance the characteristics of input in the course of the training phase. The kernels will be shared with every unit which has similar feature maps. This makes CNN easy to train and less vulnerable to overfitting. It also makes the same feature to be detected independently of its location in the image. All these advantages of CNN help for efficient classification of brain tumors and also helps in predicting the survival outcome of the patients.

The survey described in this paper mainly focuses on providing an overview of the technologies which are used in the detection of brain tumor and classification. The structure of this paper is as follows. Section Ⅱ presents some of the important and related works done regarding brain tumor detection and classification. Section Ⅲ discusses various methods, results, and limitations related to the topic. Finally, the conclusion of the discussion is presented in Section Ⅳ, including some of the methodologies which help to improve the classification in forthcoming research.

2. RELATED WORKS

This section presents some of the important and related works regarding the detection of brain tumors and their classification. Starting from analysis and estimation of tumor growth, until the survival outcome prediction, the section enlightens on various different technologies that are implemented.

2.1 Brain Tumor Growth Estimation

The author Lamia Sallemi in [3] has used the dataset of BraTS 2012, which consists of 35 pathological cases with various MRI samples. A non-parametric fast distribution-matching segmentation technique is implemented. In the next step, the estimation of the tumor growth is performed in the segmented tumor regions by using cellular automata and fast marching approach [3].

The population of cells will be estimated based on their growth using the above approaches, and hence the tumor growth is analyzed. This proposed system obtained a maximum accuracy of 97.1%. The results which were obtained were again reviewed by the clinical staff.

Advantages:
The Region of Interest (ROI) extraction and tumor growth estimation have been carefully done. This reduced a certain gap between clinical practices and advancement in technologies, thereby helping radiologists for their diagnosis and clinical decisions.

Limitations:
If the initial input image presented is of poor quality, the system suffers problems with respect to its curves and also the boundary, which will affect the segmentation and estimation steps.

2.2 Brain Tumor Classification Using Deep Learning

Classification of different types of tumors from brain images using deep learning methods has shown in [5] by Justin S. Paul. Fully connected networks and the CNNs were the neural networks used for classification. Random Forest (RF) was also used to compare the result. The system successfully classified the three tumor types with the accuracy of 93% for meningioma, 93% for glioma, and 91% for pituitary tumors.

Similarly, the RF classifier was also implemented by Chao Ma in [7]. The RF architecture has achieved an accuracy of 90% in segmentation.

Advantages:
As demonstrated in [5], [7] the proposed system effectively classified substructures in brain tumors and achieved robustness.

Limitations:
A large requirement of training data is needed for the model [7].

2.3 CNN based Tumor Classification

The author Hossam H. Sultan in [8] proposes a model in deep learning based on Convolutional Neural Networks (CNN). The main focus was on classifying different brain tumors such as meningioma, pituitary, and glioma tumors. Also, the model distinguished between several glioma grades. The proposed CNN architecture had 16 layers consisting of the input layer, convolutional layers, and the output layer. Overfitting was avoided by using dropout layers. Accuracy of 97.54%, 95.81%, and 96.89% have been obtained for classification of meningioma, glioma, and pituitary respectively [8]. Also, 100%, 95%, and 100% accuracy have been achieved for classifying glioma Grade II, glioma Grade III, and glioma Grade IV respectively [8].

Advantages:

A segmentation free approach is used and the tumor images are classified directly.

Limitations:

Reusability of the proposed architecture is not possible for classifying images with fewer numbers, which is one of the drawbacks of the deep learning methods.

2.4 Predicting Overall Survival Outcome Using SVM

The author Erik Chow in [2] conveys that precise survival outcome prediction and diagnosis depends directly on the quality of input medical images. Hence in order to remove the noise in the images, a pre-processing technique called 2D Denoising Wavelet Transform (DWT) method has been implemented, which refines the quality of input MRI sequences before the extraction of histogram features. Later the extracted features were combined with the denoised MR images and the age of patients which acts as training parameters. Survival period estimation is done with the help of a prediction model. The survival period was divided into 3 subclasses i.e, short-term survival of less than 10 months, mid-term survival of 10-15 months, and long-term survival period of 15 months and more. The proposed system obtained an accuracy of 66.7%.

Advantages:

2D DWT method enhanced the MR image quality which further helped to increase the performance.

Limitations:

Accuracy decreased when images and features were fused to predict the survival outcome.

2.5 Random Forest Based Survival Period Outcome Prediction

The author Ahamad Chaddad in [4] has used The Cancer Imaging Archive (TCIA) dataset. Experiments were done using expanded features of the Joint Intensity Matrix (JIM) to predict the survival outcome using T1-weighted, Fluid Attenuation Inversion Recovery (FLAIR), and T2-weighted T1-weighted post-contrast MR images. The Wilcoxon test is employed to study the parameters obtained from the extracted features that are used to compare the mutant and wild gene groups. Kaplan-Meier estimator is used in order to compare long and short survival patient groups. The RF classification is applied to predict the gene status and the survival outcome. The classification combining all the features resulted in an accuracy value of 86.79%.

Advantages:

The obtained accuracy suggests that the classification based on JIM and RF is more efficient than many other techniques that were used in the task of survival outcome prediction.

Limitations:

The proposed system lacks in learning discriminative features directly from the data, unlike other deep learning techniques.

3. OVERVIEW OF THE SURVEY

Several types of research have been conducted for efficient classification of brain tumors and survival outcome prediction. Some of the most popular ones are listed in Table 1.

Table -1: Survey of Various Techniques Used In Brain Tumor Segmentation, Classification And Survival Outcome Prediction

Author	Datasets	Pre-processing / Segmentation technique	Architecture	Results/Efficiency	Limitations
Lina Chato [1]	BraTS (2017)	Discrete Wavelet Transform (DWT) Otsu's thresholding method (ROI Extraction)	CNN, Linear discriminant Classifier.	73% by using a Linear Discriminant classifier.	Dataset used was a noisy dataset which reduced the accuracy
Erik Chow [2]	BraTS (2017)	2D DWT	SVM Algorithm	66.7% by using (the daubechies 2 level 3) Not more than 40% accuracy is obtained when features+age were combined	Concentrated only on glioma type tumors. Accuracy became less when images and features were fused.
Lamia Sallemi [3]	BraTS (2012)	Non-parametric fast distribution-matching approach	Cellular automata, Fast marching method.	97.10%	When the presented initial image is of deficient quality, it could affect the segmentation step.
Ahmad Chaddad [4]	TICA - The Cancer Imaging Archive	Wilcoxon rank sum test, Kaplan-Meier estimator	Random Forest Algorithm	86.97%	TICA dataset used has relatively less number of subjects for analysis (n = 107)
Justin S. Paula [5]	A public dataset-Nanfang Hospital,China	Vanilla Data Preprocessing	Random forest, CNN architecture	93% for glioma, 93% for meningioma, and 91% for pituitary tumors.	Neural networks that train on coronal and sagittal plane images are not done.
K.Bhima [6]	Tianjin Medical University, China	Marker-based Watershed Algorithm, Denoising using filters	Watershed Algorithm	97.34%	Specification of the tumor types is missing.
Chao Ma [7]	MRI datasets, left atrium, and caudate nucleus datasets	Regularization technique, Data augmentation	Concatenated and Connected Random Forest architecture	90% - complete tumor region, 80% - tumor core, 73% - enhancing tumor region.	The proposed model requires a large number of training data that are labeled.
Hossam H.Sultan [8]	The cancer imaging archive (TCIA) dataset	Regularization technique, Optimization algorithm	CNN architecture	96.13% using CAD systems, 98.7% using deep neural networks.	Concentrated only on the detection and classification of tumors but not on the survival status of patients.
Jason J. Corso [9]	GBM studies of 20 expert - annotations.	Weighted aggregation algorithm - Multilevel segmentation, Saliency-Based Extraction, Model-Based Extraction	Bayesian model-aware affinity calculation	96%	The failure modes are not addressed to consider the method for the implementation in the real-world.

4. CONCLUSION

This survey provides an overview of many different techniques that are employed in brain tumor classification and prediction of survival outcomes. In the last few years, we have seen a shift from handcrafted traditional ML methods to the end-to-end trained CNNs. Since CNN has proven better efficiency than other techniques, it is the recommended approach for medical image analysis. This approach has been reproduced by a large group of papers in this survey and thus it can be optimistically stated that this is the present standard practice.

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