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DEEP LEARNING APPROACHES FOR BRAIN ABNORMALITIES DETECTION ON MAGNETIC RESONANCE IMAGING: A REVIEW

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Abstract: In recent days, Magnetic Resonance Imaging (MRI) has played a major role in the field of medical imaging. Segmentation of MRI datasets helps in brain abnormalities detection by improved understanding, predicting the growth rate and enhanced treatment planning. Manual segmentation is identified to be more time consuming and sometimes the results are inaccurate. Automating the above task lies the real challenge owing to the problem of intensity inhomogeneity that occurs in the MRI dataset. Deep learning has been already excelling in wide ranged fields like text processing, Image Segmentation, Speech recognition, drug discovery, toxicology and various other fields. Deep learning for medical image analysis helps to integrate various ideas through their convolutional and fully connected networks. In this study we discuss about brain tumor which has its mortality level increasing at an alarming rate. In our proposal various brain tumor prediction and segmentation techniques are discussed and the best approach is compared for overall performance using various deep learning approaches.

***Keywords* – Magnetic Resonance Imaging, Brain tumor Segmentation and Brain abnormalities.**

1. INTRODUCTION

Magnetic Resonance Imaging is the most recommended technique for brain abnormalities detection. Segmentation is similar to the identification phase where it determines the signatures of the tumor observed with the original tissue concentration [1]. These tissues has various morphological parameters and signature construction is made possible by the adequate availability of the quantitative MRI data. The term quantitative is cited only when it is used for tumor classification and segmentation. Deep learning technique has emerged in the early 1990s for the medical image analysis, disease prediction and tissue classification. But then occurred the problem of over fitting and lack of training the labelled data [1]. As the time passes there evolved the large annotated training datasets enabling the work of the researchers more flexible in this area. One of the successful product of the deep learning is the convolutional neural network which can process data types like image as well as video. Brain tumor is an aggressive disease which is occurred due to the abnormal growth of cells in the brain, affecting the functions of the nervous system. These tumors are the gliomas type which has been occurred in the recent years with highest mortality rate. These are the form of neoplastic disease which comes under the brain abnormalities. Brain tumor segmentation has got various approaches to handle the segmentation easier. The dataset must have the confidentiality to be maintained. These automatic segmentation techniques are important not only for treatment planning but also helps in treatment planning and performance evaluations. For all the above reasons accurate, partially automatic and fully automatic techniques are required [2]. As these tumors are the gliomas they can be categorized as Low Grade Gliomas (LGG) and High Grade Gliomas (HGG), the former being acute and the latter being chronic. Additionally there has been an advent problem in MRI datasets. It creates Intensity Inhomogeneity [1] i.e., it provides the different intensity values for MRI dataset for the same sequence of input. Segmenting the tumor tissues as outliers is no longer an easier task because of the variable shape and the location of the neoplasms. These image intensity profiles often intersect with the neighboring normal tissue due to bias field artifacts. Even though there are various approaches has deep learning approaches for brain tumor diagnosis, a complete tumor detection system with localizing the tumor has not yet discovered. This study will act as milestone for the future enhancements. Although CNN is not a new approach, it has developed phases and deeper models embedded in it [3].

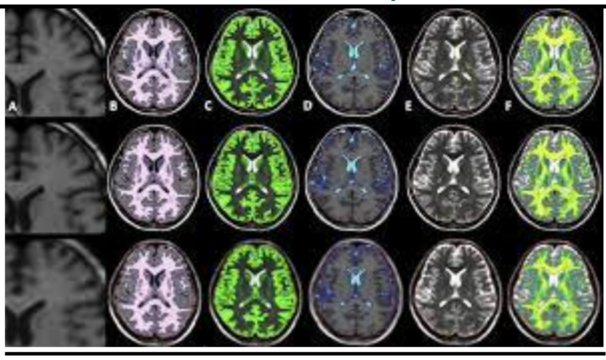

Fig 1. Brain Segmentation

Brain anomalies detection has got a good amount of research attention in past twenty years. Methods like discrete Wavelet Transform (DWT), Fuzzy C Means (FCM), and Probabilistic Neural Networks (PNN) where the first kind of approaches innovated in the field of medical Imaging. Recent trending researches through as AlexNet, ResNet, Visual Geometric Group (VGGNet) where found to be providing extremely successful results. The Idea behind this proposal is three-fold. To understand how the different architectures has been evolved, to discuss various strategies used in the approaches, to examine their results using the public datasets and finally to present an overview on future CNN.

2. OVERVIEW OF THE DEEP LEARNING APPROACHES

2.1 Fully automatic Lesion Localization and characterization: Application to brain tumors using Multi parametric Quantitative MRI Data.

Brain tumors comes with two major concepts: Lesion localization and Lesion characterization. The quantitative MRI data collected for this study is combined with advanced multivariate tools to design a fully automated system that performs both localization and characterization. Probabilistic mixtures from the conventional distributions are also taken into account for differentiating the tissue types and identifying the heterogeneity of lesions. The features are extracted from these mixtures and are modified into signatures. These signatures are clubbed together to construct a finger print model that captures the characteristics and the variability among the lesion tissues. The most possible effort has to be put on building the observed parameters into a distributed model as they may of high significance. In addition to parameter interaction, accurate lesion localization becomes the most challenging one. In this approach, the lesions are viewed as outliers with respect to the constructed distributed model. Parameters maps are built so as to avoid complications like preprocessing, post processing, bias field correction, etc.., The Fingerprint model helps to characterize and classify a subject into their respective classes [7]. As a part of supervised learning, different models are compared for their accurate prediction of the label. To predict the label ROI is first determined. The obtained ROI helps to extract the signature where the finger print model provides an associated label for the accurate classification. These quantitative MRI helps to compare measurements between subjects and the healthy population. This idea was implemented on MRI dataset collected from the rats suffering from brain tumor. Abnormal lesions are clustered under similar class with same MR parametric values. Further evaluation of lesion detection helps to obtain better results. This study is limited to the tissues with whole signal intensity [8]. The follow up of this work to prove that quantitative MRI Images has utility on Human data.

2.2 Brain tumor Segmentation using CNN in MRI Images

Gliomas are the most aggressive form of brain tumor which has got very highest mortality rate where the life expectancy is no longer than 14 months after diagnosis. The accurate segmentation helps for treatment planning and for other future evaluations. Although many methods are developed these automation segmentation has always remained a challenging task because of the varying size, shape, structure and location of the gliomas [9]. Additionally, MRI Images have an abnormality called intensity inhomogeneity where it produces different intensity ranges for the same set of MRI dataset. Being abnormalities these gliomas can be segmented as outliers but are subjected to structural constraints. Another set of classes directly learns from the dataset. Training stage of gliomas dataset is not so efficient as these gliomas does not follow a regular pattern.

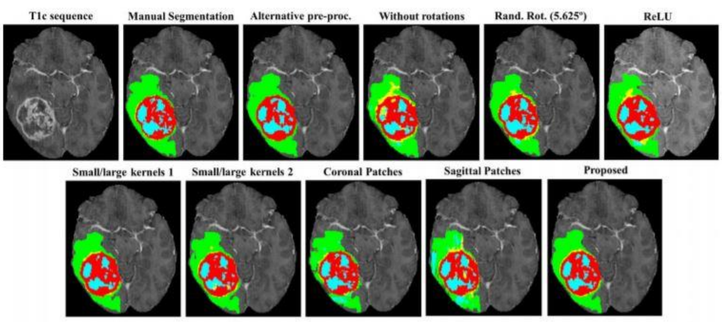

Fig 2. Segmentation with cross validation

Simultaneously it has even got some disadvantages like applying more nonlinearities and completely far from the problem of over fitting. The issue of intensity inhomogeneity addressed above can be overcome by Intensity normalization. MRI dataset requires preprocessing as they are altered by bias field distortion. It may vary even if it the sequences are obtained from the same patient in the same device at different time frames. After normalizing the mean and standard deviation are computed for each patches which are extracted to have standard mean and variance. If the convolutional layers are stacked one above the other the feature vectors become more abstract as the depth increases [10]. The evaluation was considered with three metrics such as sensitivity, specificity and accuracy. Brain tumors have varying volumes in the intra-tumoral structures. Data Augmentation is performed to balance the number of dataset available under each classes. Considering the working of CNN it has used large filters and shallow architectures for exploring several layers in the dataset. It is analyzed that using shallow architecture always resulted in lower performance.

2.3 Similarity Measure- Based Possibilistic FCM with label Information for Brain MRI Segmentation.

This study has been proposed to improve the segmentation performance of the MRI Images through Fuzzy C Means (FCM) method. This method is more effective for data clustering. But, FCM based methods suffer from Cluster-size sensitivity which comes through. Additionally, this method preserve image details and also denoises the image with the help of local label information. The process behind clustering is it generally splits the objects and patterns into varying clusters where similarity in the same class is higher and similarity between different classes is very lower [11].

Possibilistic Fuzzy C Means (PFCM) are less sensitive to outliers than FCM. PFCM can be viewed as the combination of PCM and FCM. FCM is an iterative process where it clusters n data points into c Clusters. This method makes use of Euclidian distance mainly the distance between the data points and the cluster centers. From this analysis we can understand that each class tends to have a similarity measure called intra-class similarity, similarity between classes is inter-class Similarity measure. Introducing the label Information, each MRI Images contains different noise levels and so it is necessary for FCM to utilize the adjacent information for improving the noise tolerance. PCM, IFCM, and ETFCM are sensitive for intensity and noise related problems and so they fail to classify the pixels. This method arrive at the conclusion for cluster-size sensitivity problem.

2.4 Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network.

This approach explains the difficulty in segmenting the tissues into affected and unaffected tissues. This is in accordance with gray level co-occurrence matrix (GLCM) for extracting the features and the classifier used is Probabilistic Neural Network (PNN). Performing the pre-processing step helps in improving the quality of the MR Dataset and makes these images usable for future experiments. Next process involved in this approach is segmentation. Segmentation is the process where the original image is partitioned into different sub-regions. Segmentation must have certain conditions to satisfy. The segmented pixels should lie within the region. Region Growing plays a major role in this approach. It is either grouping of pixels or grouping the small regions into larger regions. The ultimate goal is to select a seed of points from the segmented region. Morphology deals with the study of boundary area. It is the process of rearranging the pixels in the selected region.

Feature extraction involves extracting features like color, shape, intensity, texture and so on. Feature extracting methodology used in this framework is Discrete Wavelet Transform. This technique is used to analyze different frequencies at different scales. It is a powerful tool which extracts the coefficients the wavelet from brain MRI. The information about the signal function is extracted which is the basic requirement of classification. Feature extraction using Gray Level co-occurrence matrix (GLCM) [12] easily differentiates normal and abnormal tissues which are not visible to human eye perception. It provides highest accuracy by choosing the best features for easy and quicker diagnosis. It is a 2D histogram where the frequency plays a major role. In this study, preprocessing is used to remove the noise and mainly to improve the peak signal to noise ratio (PSNR). These brain abnormalities detection seems to be very fast and accurate compared to those done by the clinical experts. In Addition to the speedy detection of the tumor it also helps in identifying the precise location of the tumor. In future works, higher end classifiers can be used to increase the performance by combining different extraction techniques.

2.5 A Hybrid feature Extraction Method with Regularized Extreme Learning Machine for Brain Tumor Classification.

This study discusses about various possible techniques in traditional practices. Sompong and Wongthanavasu [13] proposed a combination of idea with fuzzy c-means algorithm and cellular automata. This method used (GLCM) as a similarity function. Another proposal uses the circularity feature to extract the tumor from the brain MRI. The proposed architecture aims at identifying the type of brain abnormalities. An approach uses GIST descriptor with Principal Component Analysis to extract the most important features without any process of segmentation. ReLM Classifier is used as regularizer to avoid the over fitting problem.

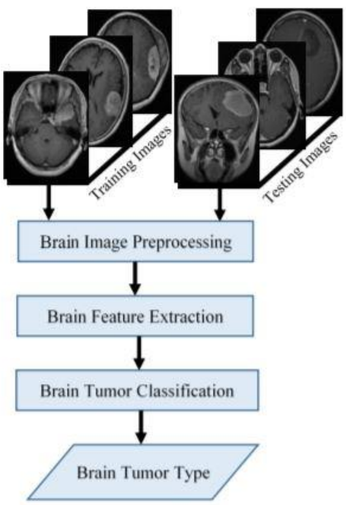

Fig 3. Proposed Workflow

GIST, a feature descriptor is used as scene classifier is combined with PCA. The values of these parameters are selected using the grid search algorithm. The brain images are converted into intensities by the process of pre-processing. It is observed that the proposed PCA-NGIST feature extraction technique seems to perform better than PCA-GIST, GIST, NGIST methods.

2.6 Convolutional Neural networks for multi-class brain disease detection using MRI Images.

Deep learning models has been widely used for brain anomalies detection over past few years. The pre-trained models employed in this technique are AlexNet, VGGNet, and ResNet to classify the MRI Images into 4 broad classes: normal, cerebrovascular, neoplastic, inflammatory and degenerative disease classes. Totally 1074 images/slices are taken and segmentation is performed. 42 different cases of 5 varying classes are taken as the dataset for this process. Their performance is compared for its performance and accuracy. The outcome of this model helps to identify the best approach out of all other approaches. Deep learning concepts helps to provide appropriate results with higher accuracies. The major contribution provided by the deep learning is the elimination of feature extraction phase. Sometimes there occurs a problem that absence of sufficient labelling of data which can be overcome using deep learning technique. The classification is done with 5-fold cross validation strategy.

The fully connected layer in the deep transfer learning adds dropout layers in between them to avoid or reduce over fitting. The dropout prevents the developed model from unwanted memorizing of data. Batch normalization helps the model for quicker training of the dataset by keeping all the pixel values in between 0 and 1. The process splits into two stages and was trained for 15 epochs only with last few layers attached and keeping the other layers frozen. The next stage involves fine tuning both convolutional and fully connected layer by unfreezing all the frozen layers with the additional 15 epochs.

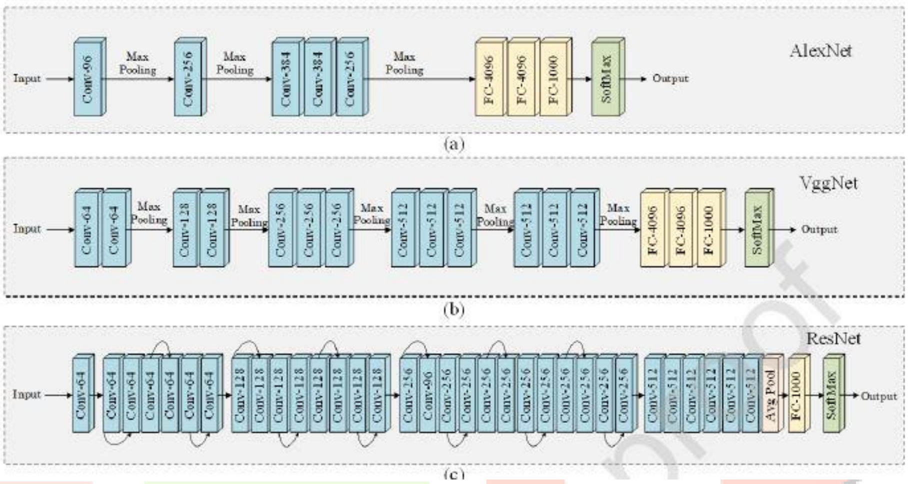

Fig 4. Deep Transfer Learning Techniques

3. Conclusion

Various techniques have been learnt from this study on segmentation in MRI. All these techniques are completely automated and does not need any manual segmentation thus overcoming the cons of some works. The subject-wise experiments cannot be extended because the datasets are not completely compatible. Fewer number of data leads to poor classification accuracy. In this study it is observed that the best classification accuracy is achieved with ResNet Architecture Model. It has got deeper layers compared to other deep learning models. The lowest performance is achieved with AlexNet. Comparing
on the basis of cost VGGNet and the ResNet models have the highest train time. The ResNet models allows to pass the information to flow through the network with intermediate connections. The experimental results show that the proposed method yields improved sensitivity, precision and recall. It is identified that deeper the architecture, highest will be the classification performance.

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