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A Review on Brain Tumor Prediction using Deep Learning

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***Abstract*— Detection and segmentation of brain tumors is important in the healthcare domain. Since brain tumors can possibly lead to cancer, it is a crucial task to detect it early through Magnetic Resonance Imaging (MRI) or Computed Tomography (CT), which are the techniques that use radio waves and magnetic fields to present a detailed view of the body organs. The images obtained from the MRI makes it hard to locate the exact position of the tumor and hence it is a challenging task to detect the tumor accurately. Thus, computer-aided methods (segmentation, detection and classification processes) with better accuracy are required for early tumor diagnosis. The segmentation of brain tumor which is usually carried out manually by the radiologists through their expertise and skill is a highly prolonged task and there can be chances of some faulty predictions, hence, the semantic segmentation is proven to be an effective method to overcome this problem. Semantic segmentation method is applied to brain tumors which are automatically segmented with the aid of deep learning techniques (CNN, RNN, GAN, LSTMs, etc.). The usage of deep learning techniques with greater accuracy and robustness are proven to be effective for the precise diagnosis of brain tumor. The primary objective of this paper is to examine the previously published techniques using deep learning for the human brain tumor prediction.**

Keywords*—*Deep Learning, Brain Tumor detection, MRI, Convolutional Neural Network (CNN), Semantic segmentation

I. INTRODUCTION

All human biological processes are managed by the brain, an organ located inside the skull. It is one of the complex and the most important organs of the human body which is responsible for controlling and coordinating most of the processes that regulate our body.

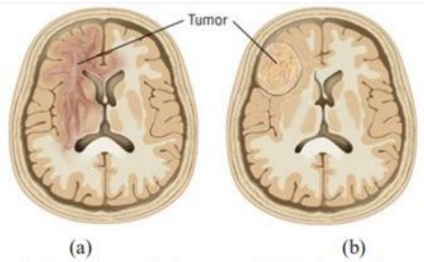

Fig. 1 (a) malignant brain tumor; (b) Benign brain tumor

Fig. 1.Types of Brain Tumors [26]

The formation of extra mass of cells in the brain is referred to as brain tumor. These brain tumors can primarily be classified as non-cancerous (benign), and cancerous (malignant), as shown in the above Fig. 1 [26]. Brain tumors will either originate within the human brain known as primary brain tumors, or will originate in different regions of the human body and can further spread, or, metastasize to the brain as secondary (metastatic) brain tumors. Gliomas are the general categories of brain tumors. These kinds of tumors begin within the brain or the spinal cord.

Early detection of brain tumor is essential as it can show certain side effects, such as memory loss and cognitive issues, and can be fatal. The brain tumor diagnosis usually starts with Magnetic Resonance Imaging (MRI) which creates precise images of the brain with the help of magnetic fields. MRIs are commonly preferred to diagnose a brain tumor since it produces more detailed images than Computed Tomography (CT) scans.

The radiologist's skill and experience are the primary factors in manually segmenting the MRI images of the brain performed by medical professionals. Thus, manual segmentation is a very laborious process that takes a lot of time, usually involving longer procedures, and the outcomes are heavily reliant on human expertise. Furthermore, these results differ from expert to expert and hence, manual tumor segmentation will have an adverse negative impact on early brain tumor diagnosis and treatment.

Automatic segmentation techniques or algorithms can be employed on MRI images as they deliver reliable outcomes and are measurable, preventing user-based errors. Since, brain tumors can develop at any time and can take the form of any shape, size, or contrast; it is a tricky process to automatically segment brain tumors. Therefore, DL (deep learning) techniques are proven to be suitable and effective for the detection of brain tumors.

Deep Learning (DL) Networks can generate several layers of abstraction by developing computational models that constitute many processing layers. These algorithms process the unstructured data (text & images), and the feature extraction procedure is automated, which reduces human intervention and facilitates in overcoming the limitations of automatic and manual segmentation.

The tumor diagnosis can be made accurate with the application of CNNs. CNNs takes a source input, convolutes it with a kernel (a filter) and produces the required output. The deep learning method known as semantic segmentation, which

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allocates a class label to all the components of an image (pixel), can be applied using CNNs. Semantic segmentation is comparatively more accurate technique than other methods of object detection as it assigns labels to image pixels.

Contribution: We have surveyed the existing research works in the field of detection of Brain Tumor using deep learning. We have examined the different methodologies used in the respective solutions in the works and have put forward them in a lucid manner.

Paper Organization: The organization of the remaining sections of the paper is as follows. Section II is the literature survey of the research papers. Section III is the conclusion. Section IV is the references for the survey done.

II. Literature survey

N. Bahadure et al. [1] developed Berkeley wavelet transformation (BWT) to enhance the efficiency of medical picture segmentation. Furthermore, the important features are extracted from each segmented tissue to increase the support vector machine (SVM)-based classifier's quality rate and accuracy. The outcomes achieved a sensitivity, accuracy, and specificity of 97.72 percent, 96.51 percent, and 94.2 percent, respectively, demonstrating the best outcomes for the aforesaid technique for distinguishing between diseased and normal tissues from brain MR images. With an average Dice Similarity Index of 0.82, radiologists' automated and manual tumor areas have a good amount of overlap.

S. Kahali et al. [2] developed a 3D brain picture segmentation method called 2-stage fuzzy multi-objective framework (2sFMoF). A new native membership performance along with the global membership performance for each voxel are defined in the initial step of the 3D abstraction fuzzy c-means (3DSpFCM) formula by combining the cube like neighborhood data of the degree information. The final cluster prototypes are created by feeding the obtained cluster prototypes into a 3D-changed fuzzy c-means (3DMFCM) algorithm that also uses native voxel data. In terms of qualitative and measurable features, the predicted technique's performance is compared to that of alternative competent ways and found to be better.

A.B. Rabeh et al. [3] proposed a unique computerized technique of brain picture segmentation that revolves around the Corpus Callosum (CC) and the Active Contour (AC) model to extract the hippocampus for determining Alzheimer's disease. Their primary contribution was the integration of the geometric method and the AC's statistical method. To create an average shape and automate the initialization operation, the Caselle Level Set was combined with a learning phase. The level set concept was used at the contour evolution stage. They saw encouraging results with the modified level set, which was a combination of two techniques. The updated level was used to calculate the standard deviation, feature surface, and perimeter.

J. Nayak et al. [4] focused on FCM methods and carried out a comprehensive survey on them. FCM has been used in various image analysis related applications due to its dynamic nature. This study has limitations. The survey includes the collection, summarization, and labeling of FCM applications, is in itself a complex task. This paper provides a concise overview of FCM while describing limited previous knowledge in order to draw conclusions about how FCM and its uses have changed over time. Despite its limitations, this paper has provided a brief overview of how FCM and its applications have evolved.

W. Zhang et al. [5] came forward with deep CNNs to separate iso-intense stage brain tissues (baby brain tissues) into white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF), employing multi-modality Magnetic Resonance Images, which is crucial for understanding early brain development in both health and disease. Results revealed that, when it came to segmenting baby brain tissues, CNN outperformed earlier techniques. The inquiry about CNN seems to offer more exact and quantitative computer modeling and comes about for the division of infant tissue pictures. In this paper a few slices (2D images) were segmented manually and if labeled data were available, CNN can be used for 3D image segmentation.

X. Fu et al. [6] put forward and recommended a CNN for the segmentation of microscopic pictures (tissues and cells). The network consists of eleven consecutive normalization layers that have been convolutionally corrected. With a Dice Similarity Coefficient of 0.947, it outperformed cutting-edge CNNs on cardiac histology image dataset (labeled fibrosis, background and myocytes). It can also be smoothly trained from beginning to end and keeps image resolution while capturing fine-grained information. The learning data should include traits from the entire image collection, traits from each class, and color variations in specific structures for optimal results.

P. Mlynarski et al. [7] suggested a CNN model that integrates the advantages of the long-range 2D and the short-range 3D context. The imposed architectural model solves the issues of the missing MR images in the course of the training period. A hierarchical decision model is used to aggregate the results of different segmentation models in order to get beyond the restrictions of certain neural network architectural choices. Finally, a quick and effective training algorithm for big CNN models is shown. This technique yields accurate Dice Scores of segmentation of total tumor, tumor core, enhancing core are 0.918, 0.833, 0.854 respectively.

S. Maharjana et al. [8] pointed to enhancing the classification exactness by diminishing the hazard of overfitting issues, supporting multi-class classification, and centering on the classification exactness of the diverse sorts of tumors from the 3D MRI pictures. The proposed framework comprises CNN with an altered Softmax loss function and regularization. The proposed arrangement is superior compared to the other classification strategies based on a likelihood score and exactness higher than 2% of the named information and an execution time of 40–50 milliseconds less. This paper tackles the issues of two-fold (binary) classification, preparing time, and overfitting of the information.

S. Qamar et al. [9] presented a 3D U-Net variation using CCNN skip layers to get the medical and volumetric relevant information. Three phases make up the suggested architecture: the densely- linked stage, the residual inception stage, and the upsampling stage using the iSEG dataset (2017) as validation for segmentation of newborns' brains. When compared to other methodologies, the strategy yields cutting-edge outcomes. In white matter (WM), cerebrospinal fluid (CSF) and gray matter (GM) tissues, the proposed strategy yields 0.905, 0.95, and 0.92, respectively as dice scores.

A. Angelopoulou et al. [10] analyzed the brain portions and established predetermined landmarks on the sections in order to rebuild the 3D surface of the ventricles using the GNG (Growing Neural Gas) method, which also eliminates noise and outliers. The accuracy of this algorithm outperforms that of the Neural Gas and Kohone self-organizing networks in terms of execution speed and quality. Additionally, 3D models of the ventricles are created using this method. This method also speeds up the conventional surface restoration and filtration processes.

T. Heimann [11] focused on reviewing the techniques (automatic detection of shape correspondences) to create and employ 3D Statistical Shape Models. The paper also suggests alternate methods for statistical modeling. It included how to represent shapes, how to build models, and how to make them look similar to the real thing (shape correspondence) and also providing the current overview of the state.

T. D. Bui et al. [12] provided an accurate volumetric infant brain MRI segmentation approach based on a DenseNet, in order to address the low intensity contrast across tissues, the paper has to produce very accurate segmentation results, fully convolutional DenseNet along with skip - connections is specifically intended to allow the direct combination of various layers of dense blocks. The suggested network, known as 3D-Skip Dense Segmentation, is used for segmenting the brain tissue of a 6-month-old newborn using MRI. The projected network and the current architecture's resilience were evaluated using the iSeg-2017 dataset. The proposed 3D-Skip Dense Segmentation method outperformed the 21 competing teams in the dataset.

L.Wang et al. [13] described a Novel Patch Driven level set technique since infant brain MRI segmentation is difficult. The introduced method makes utilization sparse representation techniques to segment neonatal brain MR images. The major emphasis of the paper is the segmentation of newborn brain imaging into general WM, CSF, and GM. The introduced method was thoroughly tested on 132 extra testing individuals in addition to 20 training subjects using cross validation (leave one out). The method suggested in this work attained a high accuracy of 0.919 ± 0.008 for WM and 0.901 ± 0.005 for gray matter GM.

M. Amian and M. Soltaninejad [14] proposed a computerized method for 3D Deep Segmentation is proposed for the detection of gliomas in 3D MRI scans. Then, a survival prediction is done with the help of an algorithm based on random forests (RF). U-net along with skip layers was suggested for fine medical picture segmentation. For the goal of survival prediction, the segmentation's output masks are taken as the input. The algorithm is implemented using Keras Tensorflow and MATLAB 2019a for segmentation and classification tasks, respectively, and is trained on the BraTS 2019 dataset. The outcomes indicate that the suggested methods offer viable segmentations and survival prediction.

S. Alqazzaz et al. [15] applied a FCNN SegNet on 3D datasets for 4 MRI modalities. This algorithm, for precisely segmenting a brain tumor attempts to locate the complete tumor volume and divide it into four sub-tumor regions. The proposed approach consists of four basic steps: (i) Data pre-processing; (ii) SegNet network-based image segmentation of brain tumors; (iii) Post-processing; (iv) SegNet_Max _DT. To evaluate the suggested approach, the Brain Tumor Segmentation 2017 (BraTS 2017) dataset is utilized. The presented algorithm was put into practice using MATLAB 2018a, and the segmentation outcomes were quantitatively assessed using the F-measure (evaluation metric). The outcomes show that this suggested methodology is capable of totally segmenting the tumor and sub-tumor regions automatically.

Li Sun et al [16] has given an approach in which the brain tumor detection and survival prediction is finished primarily with the assistance of deep learning - based frameworks. BraTS 2018 dataset was utilized to implement segmentation and survival prediction in order to boost the performance and scale back the bias within the result. Tumor segmentation was done with the help of 3 totally different 3D CNN architectures by a principle called voting. A Decision Tree model of regression was used with gradient boosting for the variance reduction. To pick the best range of strong options Cross Validation was applied. The survival of patients was expected by training the Random Decision Forest model. Results of Survival Prediction were 61 percent correct and classified the survivors as short-term, mid-term and long-term survivors. The obtained results were analyzed and a conclusion was drawn that the single models have weaker performance when compared to collective models.

U. Baid et al [17] has given an approach in which the 3D U-Net design was accustomed to segment numerous radiologically specifiable sub-regions like lump, enhancing tumor, and sphacelus. This design has been enforced using the Tensorflow library. The DCNN-primarily based design was accustomed for capturing the context (contracting path) and to observe the precise localization of the tumor. To train the 3D U-Net design, 3D patch extraction was done from BraTS dataset (training). The results of this approach show the importance and use of patch-dependent 3D U-Net for segmenting tumors accurately. This study shows that a weighted patch-based segmentation approach is healthier in terms of performance in comparison to the pixel-based approach.

D. Ataloglou et al. [18] formulated a completely programmed division framework with incredible exactness that comes about with the help of Deep Learning procedures. CNN is used in the suggested paper, along with specific segmentation and error correction processes. By merging numerous datasets through transfer learning, they investigated various training methodologies utilizing CNN-based segmentation, which enhances segmentation quality. Utilizing two isolated open datasets, the proposed strategy was assessed and compared favorably to the existing strategies. A mean Dice value of 0.9015 was obtained in the EADC-ADNI HarP dataset when comparing the output of the approach with the ground truth manual tracings, whereas 14.8 seconds were needed to segment a whole MRI volume.

A.M. Hasan et al. [19] focused on identifying the tumor slices in the images in volumetric scanned MRI images. The gathered data is cleaned and standardized using a variety of algorithms and pre-processing steps. ANOVA and a modified gray-level co-occurrence matrix were used for feature extraction and selection. A multi-layer perceptron is used to segment the brain tumors from the scanned images. A dataset of 165 patient images from Teaching Hospital in Iraq was used for this research. When compared to manual techniques, the segmenting tumors had an exactness of 89 percent (4.7%).

Y.Zhu and C. Huang [20] proposed an effective method based on adaptive histogram. Information entropy in this algorithm remains constant. A parameter called 'β' was introduced in this algorithm. The algorithm also intakes the information entropy as an aimed function in order to fine-tune the spacing between two gray levels. This is found to be useful in CT image processing. The proposed algorithm in this paper identifies the gray type image, selects the β parameter and the value of the image is improved. The criteria for the choice of parameter β in diverse conditions and finding the gray-type are also presented in this paper. It can be concluded that this improved algorithm showed improved visual effects and is helpful in CT image processing techniques and also the details of the image are retained by avoiding false contours and bright local areas.

G. Jimenez et al [21] introduced 2 deep learning architectures to proficiently find and classify the cell division in an exceedingly histopathological tissue sample. The datasets utilized for this include those employed in the ICPR-2012 contest. The primary technique has 2 elements, involving a pre-processing of the histopathological tissue image and a CNN used for classification (binary). The projected technique achieved accuracy of 95 percent in testing, the F1-score being 94.35 percent. The second approach involves the employment of semantic segmentation. The projected technique achieved an accuracy of 95 percent. Some methodologies specifically, Alex-Net and U-Net were adapted to compare and verify its relevance in segmentation and classification. The results show that the performance of DL (deep learning) approaches tends to improve the accuracy by nearly 7 percent. The U-Net approach is taken into account and is found to be more precise than the Alex-Net approach.

R.Martins et al [22] explored the issue of multi-modal segmentation of image, and have proposed an innovative metric to influence the contour and global accuracy. The proposed metric is evaluated. In this paper, the issue of discovering one accurate system of measurement that is intended for global-classification of pixels and better segmentation of contour is addressed. Also a new system of measurement is proposed with the help of Jaccard index. The new metric introduced in this paper for supervised segmentation is found to calculate the quality and value of the segmented regions along with their boundaries. The proposed system of measurement includes the rate of suitably labeled pixels & helps in achieving better results for semantic segmentation.

M. Sokolova and G. Lapalme [23] have visualized 24 performance procedures used in the classification tasks of ML which include multi-class, binary, hierarchical and multi-labeled. The research showed that the assessment of classification outcomes might rest on the invariance assets of the procedures. These properties permitted satisfactory divisions in the connections between the procedures. The measure invariance taxonomy was constructed to match the procedures with data features with regard to each label delivery variations in classification issue. Visualizing the applications of various performance procedures on diverse subfields of classification of text is carried out in this research. The results show the invariance taxonomy measure in regard to every applicable label delivery variation in classification issues.

Z. Liu et al [24] introduced a consistent architecture with the aim to speed up the working of both 3D and 2D CNNs. The convolutions have been mapped to matrix multiplications here. In order to re-design a convolutional layer, a splitting strategy was adopted to regulate the memory capability. With the intent of computing the matrix multiplications, a 2D MAC [Multiply and Accumulate] array is utilized. An image (accelerator) with High Level Synthesis was enforced and this accelerator was tested on 3 of the CNN models namely: Alex-Net, 16 layer VGGnet, and 3D graphics technique called C3D. A cost-effective matrix mapping module is projected so as to avoid information replication throughout the convolutional windows. Tentative results obtained show that the accelerator achieves progressive output performance on each 2D and 3D CNNs, with a lot of improved energy effectiveness when compared with the C.P.U. and GPU. This paper concludes that the design introduced fully utilizes the resources for computation and states that this explicit application can be often used with ASIC implementations.

A. Erdamar et al [25] presented a deep learning based method called CNN in order to classify the single cell electrophoresis images. This technique was used to demonstrate the usefulness of Deep Learning algorithm on the images of cells. In this, the CNN which has been used is tested and trained with huge accuracy. Results obtained demonstrate that the CNN Network algorithm was used to categorize 5 diverse scores of single-cell electrophoresis images successfully. This analysis algorithm used for images in this study was evaluated by MATLAB(R). The CNN algorithm used in this work has shown the results like high sensitivity, specificity, and accuracy. This study shows that CNN can quantitatively regulate the comet assay scores.

TABLE I. COMPARISON BETWEEN DIFFERENT METHODLOGIES

Sl No.	References	Algorithm / Methodology	Results / Conclusion
1	[1]	- Berkeley Wavelet Transformation (BWT) - SVM Classifier	The results are as follows: 94.2% - specificity, 96.51% - accuracy, 97.72% - sensitivity 0.82 – DSC
2	[14]	-Automated method for 3D Deep Segmentation -Random Forest Algorithm	For predicting survival rate, the overall accuracy obtained: 49% - test dataset, 52% - validation dataset
3	[26]	- Automatic Segmentation - K-means clustering - SVM Classifier - Naïve Bayes	K-means clustering technique – to segment the brain tumor SVM & Naïve Bayes – classifiers used to segment final findings. Efficiency Percentage of Histogram Normalization is as follows: Naïve Bayes = 0.8723 SVM = 0.9149
4	[27]	- Convolutional Neural Network (CNN) along with SVM classifier - Activation algorithms (softmax, RMSProp, sigmoid, etc)	Using RMSProp as optimizer and Softmax as final layer of the neural network, Accuracy achieved is 99.74%.

III. CONCLUSION

Depending on user participation, different types of brain tumor segmentation techniques exist, they are as follows: manual, semi-automated, and automatic.

In this surveyed paper, fully automated segmentation techniques are prioritized, since the manual segmentation techniques have significant drawbacks. Majority of current investigation on brain tumor segmentation is principally centered on automatic techniques. Exploitation of fully automated segmentation techniques will maximize the accuracy rate and minimize the error rate. These techniques embrace SVM, K-Means, ANN, CNN, etc. When compared to other methods, our research demonstrates that the CNN algorithm achieved the highest accuracy and precision rate, which was approximately 99.74% as observed from the above table. Hence, applying CNN model is observed to provide more accurate results in tumor detection. It was additionally brought to our observation that deep learning techniques have gained interest so as to enhance the accuracy and transparency of tumor prediction.

Hence, the implementation will be carried forward with CNN technique with the usage of Jupyter Notebook or Google Colab, which includes predicting the type of tumor using real time dataset.

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