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SURVEY

Comparative Study on Architecture of Deep Neural Networks for Segmentation of Brain Tumor using Magnetic Resonance Images

R. PREETHA, M. JASMINE PEMEENA PRIYADARSINI, AND J. S. NISHA
School of Electronics Engineering, Vellore Institute of Technology, Vellore, Tamil Nadu 632014, India

Corresponding author: M. Jasmine Pemeena Priyadarsini (jasmin@vit.ac.in)

ABSTRACT The state-of-the-art works for the segmentation of brain tumor using the images acquired by Magnetic Resonance Imaging (MRI) with their performances are analyzed in this comparative study. First, the architectures of convolutional neural networks (CNN) and the variants of U-shaped Network (U-Net), a kind of Deep Neural Network (DNN) are compared and their differences are highlighted. The publicly available datasets of MRI images specifically Brain Tumor Segmentation (BraTS) are also discussed. Next, the performances of tumor segmentation of various methods in the literature are compared using the parameters such as Dice score and Hausdroff distance (95). This study concludes that the U-Net based architectures using the BraTS-2019 dataset outperform well compared with other CNN based architectures.

INDEX TERMS Brain tumor, convolutional neural networks, deep neural networks, image segmentation, magnetic resonance imaging, U-Net.

I. INTRODUCTION

The non-invasive approaches such as Computed Tomography (CT), Positron Emission Tomography (PET) and MRI are the currently available imaging techniques for the diagnosis of internal organs. The CT scan is a transmission-type imaging technique in which X-ray radiation is used to obtain the images of internal organs. PET is an emission-type imaging technique which uses a radio-active isotopes injected into the body to see the functions of organs. Since MRI is a non-harmful technique and it provides clear information about the internal body parts, it is mostly preferable to diagnose the abnormalities. The confirmation of malignancy of brain tumor through the non-invasive methods is still a difficult task, even though the techniques with deep learning models play a major role.

The structure of human anatomy can be viewed in three planes [1] namely axial, coronal and sagittal using MRI as in Fig.1 which depicts the three planes of human brain images [2]. The phenomenon behind the MRI is the electrification of hydrogen atoms in the human body with the emission of radio frequency (RF) subject to a magnetic field. Then the energy absorption by hydrogen nuclei occurs and the energy is emitted as electrical pulses whenever the RF stops. After releasing the energy, the atom is relaxed i.e., gets back into its original stage and the time required for this is called the relaxation time. The two types of relaxation time: 1) longitudinal (T1) and 2) Transverse (T2). By this, three sequences of images are obtained and they are T1-weighted

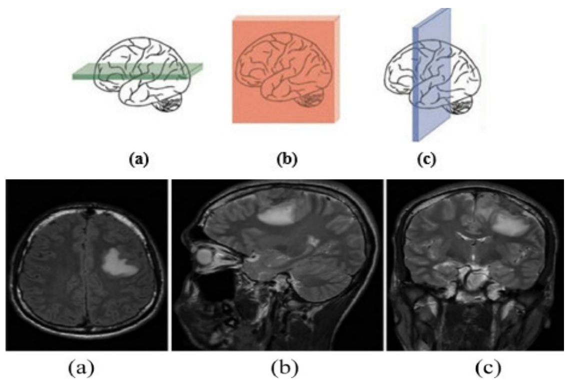

FIGURE 1. Three Planes of MRI and the corresponding images of the brain [1]. a) Axial, b) Sagittal and c) Coronal.

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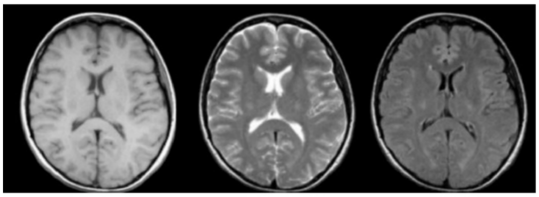
(a) (b) (c)

FIGURE 2. Three modalities of MRI Brain Images [3]. a) T1-weighted b) T2- weighted and c) FLAIR.

(T1 or T1w), T2-weighted (T2 or T2w) and FLAIR. The time taken for RF remittance and echo signal (ES) reception is called the time to echo (TE). The short TE and RT are used to generate the T1w images and the long TE and RT are used to acquire T2w images. The properties of tissues with respect to T1 and T2 decide the brightness and contrast of the acquired images and hence the TE and RT play a vital role in distinguishing the abnormalities present in the tissues.

The duration of TE and RT are long in FLAIR. The FLAIR modality gives the information of the whole tumor whereas T2 provides tumor core information (except edema).The T1c provides the details of active tumor whereas T1 provides the details of bone structures and tumor boundary.The T1, T2 and FLAIR modalities of MRI brain image [3] are depicted in Fig. 2. T1- and T2-weighted images may typically be distinguished simply by examining the CSF. On T1-weighted imaging, CSF is dark, while on T2-weighted imaging, it is bright. In FLAIR abnormalities remain bright but normal CSF fluid is attenuated and made dark. This sequence is very sensitive to pathology and makes the differentiation between CSF and an abnormality much easier. The comparison of three modalities are given in Table 1 [4].

TABLE 1. Comparison of T1w vs. T2w vs. flair [4].

Tissue	T1w	T2w	FLAIR
CSF	Dark	Bright	Dark
White Matter	Light	Dark Gray	Dark Gray
Cortex	Gray	Light Gray	Light Gray
Fat(within bone marrow)	Bright	Light	Light
Inflammation(infection, demyelination)	Dark	Bright	Bright

Radiologists focus on particularly cerebrospinal fluid space and the two matters – white and gray of the brain. Fig.3 depicts the general brain image [5] and images of three different regions of the MRI brain image [6].

Image segmentation contributes to a great extent to the diagnosis of brain tumor whether malign or benign using non-invasive methods. The segmentation approaches based on the deep learning techniques using CNNs now become the recent research works. However, CNN based techniques have convergence problems. So, the researchers tried to get good segmentation results using multimodality MRI images with the advancement of deep neural network techniques such as U-Net and its variants. Since the brain tumor is split up into whole tumor (WT), enhanced tumor (ET), tumor core (TC) and tumor area or active tumor, the segmentation of such sub regions is required.

As each modality of MRI gives different information about the tumor, the task of segmentation becomes time consuming process. This is because, it is required to take the MRI images using four modalities for the same patient and blending of four different information about one tumor. Fig. 4 shows that the brain image of one patient obtained using four modalities of MRI. However, they do not provide the same information. So, some researchers attempted to segment the sub regions of brain tumor using multi modal MRI images. Some works have attempted only to segment the abnormal portion from the fused version of the four modalities of MRI images. Some authors performed the segmentation of tumor parts individually from all modalities of MRI images and then the fusion of four segmented parts is achieved to get a single image. In the literature, most of the researchers employed the Dice score to evaluate how the new method achieves the segmentation compared to the ground truth.

II. DIFFERENCE BETWEEN THIS REVIEW AND OTHER REVIEWS

In the past few years, a number of noteworthy brain tumor segmentation surveys have been released. Table 2 lists the pertinent recent surveys together with their specifics and highlights [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24]. Among these [15], [18], and [24] are most similar. Most of the answers to the BraTS2012–2018 issues were covered by the authors in [15], [18], and [25], however there was a lack of an analysis based on technique category and highlights. The review of traditional brain tumor segmentation techniques was also the subject of survey conducted by [13]. But it does not included a technical study or a description of segmentation techniques based on deep learning. Before 2013, the majority of the suggestions for early state-of-the-art brain tumor segmentation techniques mixed traditional machine learning models with manually created characteristics, according to a survey published in [7]. A survey of MRI-based brain tumor segmentation was published in 2014 [8]. Deep learning-based techniques are not included in this survey. [24] focused on the technical examination of deep learning-based brain tumor segmentation techniques, whereas Nalepa et al.'s [14] investigation covered the impacts and technical aspects of several types of data augmentation methods with an application to brain tumor segmentation. Our study focused on the architecture of various CNN based and DNN based neural networks for Segmentation of Brain Tumor using MRI Images. Further, the benchmark datasets released from 2012 to 2021 and other publicly available datasets were discussed.

III. PUBLICLY AVAILABLE DATASETS

The researchers use a number of publicly available datasets to review the proposed methodologies. This part highlights a few important and challenging datasets [26], [27], [28], [29],

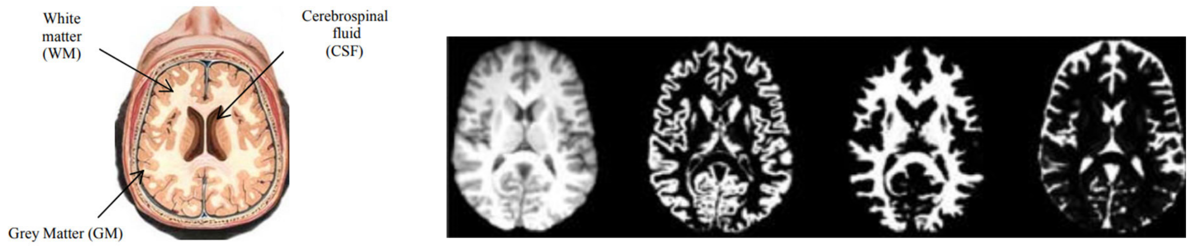

FIGURE 3. MRI brain image and its regions [5]. From left to right – General brain image with its regions, MRI Brain image, image of gray matter, image of white matter and image of cerebrospinal fluid.

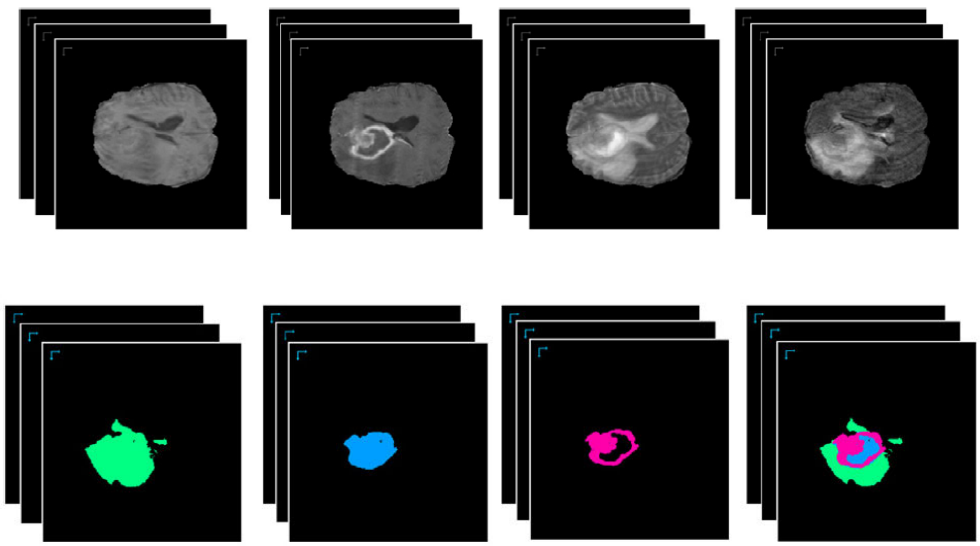

FIGURE 4. Illustration of brain tumor segmentation [90]. Top – from left to right, the images are respectively of volumetric T1, T1c, T2 and FLAIR modalities of MRI images of brain tumor. Bottom – from left to right, the images are of whole tumor, tumor core, enhancing tumor and all tumor areas.

[30], [31], [32], [33], [34], [35], [36], [37], [38]. The most challenging MRI datasets are BraTS.The BraTS Challenge is released every year and features more challenges with a resolution of 1 mm3 voxels. The state-of-the-art works using BraTS datasets of MRI brain tumor images released in 2012 to 2021 [26], [27], [28], [29], [30] are considered in this paper. The datasets contain the brain tumor images belonging to glioblastoma (GBM) i.e., higher grade glioma (HGG) and lower grade glioma (LGG). The datasets BraTS 2012 and BraTS 2013 have a smaller number of images but they are being used along with the latest datasets. Because these two datasets contained the annotations which were provided manually by the clinical experts. Since BraTS 2014, BraTS 2015 and BraTS 2016 have pre-operative and post-operative images and also the annotations were given to the fusion of segmented images using four modalities, they were discarded in the datasets released in 2017 to 2021. The BraTS - 2017, 2018, 2019 and 2020 were released for challenging the task of image segmentation and survival prediction whereas the BraTS 2021 was released for segmentation followed by the classification of brain tumor. Summary of publicly available datasets are given in Table 3 and Fig.5. BraTS datasets with time points given in Table 4. Figshare [31] brain tumor dataset containing 3064 T1-weighted contrast-enhanced images from 233 patients with three kinds of brain tumor: meningioma (708 slices), glioma (1426 slices), and pituitary tumor (930 slices).RIDER dataset [35] contains MRI multi sequence images of 19 patients with glioblastoma. The ISLES dataset [36] is a medical imaging collection aimed at improving research in ischemic stroke diagnosis and treatment. It includes MRI and CT scans, annotated lesions, and various data sources, aiming to enhance patient care and healthcare outcomes. REMBRANDT dataset [38] contains MRI multi sequence images of 130 patients with glioma types of grade II, grade III and grade IV. Different types of tumor types with publicly available dataset is given in Table 5 [33], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53].

IV. BRAIN TUMOR SEGMENTATION

The technique of separating the pixels to identify and distinguish the target area, typically a lesioned region from the surrounding and healthy tissues is known as segmentation

TABLE 2. Recent surveys related to 'brain tumor segmentation'.

Year	Work	Remarks
2013	[7]	SURVEY ON CONVOLUTIONAL NEURAL NETWORKS APPLIED TO BRAIN MRI IMAGES
2014	[8]	SURVEY ON BRAIN TUMOR SEGMENTATION METHODS USING MRI
2016	[9]	SURVEY ON BRAIN TUMOR SEGMENTATION METHODS USING MRI
2017	[10]	REVIEW ON DEEP LEARNING FOR BRAIN MRI SEGMENTATION
2017	[11]	A COMPREHENSIVE REVIEW ON DEEP LEARNING BASED MEDICAL IMAGE ANALYSIS
2018	[12]	A REVIEW ON USE OF DEEP CNN IN BRAIN IMAGE ANALYSIS
2019	[13]	A GENERAL SUMMARY OF CLASSIC BRAIN TUMOR SEGMENTATION TECHNIQUES
2019	[14]	IMPACTS OF DATA AUGMENTATION METHODS TO BRAIN TUMOR SEGMENTATION
2019	[15]	SURVEY ON BRATS CHALLENGE SUBMISSIONS DURING 2012-2018
2020	[16]	A COMPREHENSIVE REVIEW ON DEEP LEARNING BASED OBJECT DETECTION
2021	[17]	REVIEW ON BRAIN TUMOR DETECTION THROUGH MRI
2021	[18]	SURVEY ON BRAIN TUMOR SEGMENTATION USING STATE-OF-THE-ART DEEP LEARNING TECHNIQUES
2021	[19]	MULTI-ORGAN CANCER DIAGNOSIS
2022	[20]	BRAIN TUMOR SEGMENTATION TECHNIQUES OVER 2010-2020
2022	[21]	REVIEW ON CONVOLUTIONAL NEURAL NETWORKS FOR BRAIN TUMOR SEGMENTATION
2022	[22]	SURVEY ON MACHINE LEARNING, DEEP LEARNING MODELS USED ON BRATS CHALLENGE DATASETS
2023	[23]	SURVEY ON STATE-OF-THE-ART DEEP LEARNING TECHNIQUES FOR BRAIN TUMOR SEGMENTATION
2023	[24]	SURVEY ON BRAIN TUMOR SEGMENTATION USING DEEP LEARNING

in medical imaging. It is a challenging task in the case of brain tumors due to the characteristics of the tumor in the MR images [54]. Several MRI segmentation techniques have been developed based on tissue characteristics [55]. These techniques can be divided into five primary classes: intensity-based approaches, manual segmentation, atlas-based methods, surface-based methods, and hybrid segmentation methods [56]. In fact, a variety of applications in image segmentation have been established by hybrid techniques, a combination that includes two or more techniques and soft computing techniques such as fuzzy logic, neural networks, and genetic algorithms. In order to achieve economical solution cost, tractability, and robustness, soft computing exploits the tolerance for imprecision, ambiguity, partial truth, and approximation. In addition, deep learning methods are frequently used for image segmentation, which mimics the functioning of the human brain and yields quick and precise results.

Traditional image processing techniques include Thresholding [57], Region growing [58], [59], Watershed transform [60] and Active contour [61], [62]. Machine learning and deep learning based approaches include supervised learning, semi supervised learning and unsupervised learning. Unsupervised approaches for brain tumor segmentation using MRI images typically involve methods that do not require prior labeled data for training. These methods rely on the inherent properties and patterns within the MRI images to segment the brain tumors. Unsupervised techniques known as clustering-based segmentation divide an image into groups of pixels with similar brightness without using training images. Actually, clustering techniques use the existing image data to self-train. By repeating two procedures, namely data clustering and estimating the attributes of a certain tissue class, segmentation and training are carried out simultaneously. The k-means clustering [63], [64], fuzzy c-means clustering [65], [66], Markov random field [67], and expectation-maximization approach [68] are the most often used clustering techniques. This survey focus on deep learning based segmentation methods such as CNN based segmentation and U-net based segmentation.

TABLE 3. Summary of publicly avalable datasets.

Datasets	Number of slices	Sequences	Description
BraTS SERIES[26],[27]	240×240×155	T1w, T1Cw, T2w and Flair	BraTS 2012 - 50 Subjects BraTS 2013 - 60 Subjects BraTS 2014 - 238 Subjects BraTS 2015 - 253 Subjects BraTS 2016 - 391 Subjects BraTS 2017 - 477 Subjects BraTS 2018 - 542 Subjects BraTS 2019 - 626 Subjects BraTS 2020 - 660 Subjects BraTS 2021 -2040 Subjects
ISLES 2015	SISS- ISLES 230 × 230 × 154 (154 slices in each case) SPES-ISLES 230 × 230 × 154 (154 slices in each case)	SISS- ISLES DWI, T1w, T2w, Flair SPES-ISLES CBF, CBV, DWI, T1Cw, T2w, Tmax, TTP	64 Subjects
ISLES 2016	192 ×192 ×19 (19 slices in each case)	MTT, rCBV, relative rCBF, Tmax, TTP	75 Subjects
ISLES 2017[36]	192 ×192 ×19 (19 slices in each case)	PWI, ADC, MTT, rCBV, rCBF, Tmax, TTP	57 Subjects
RIDER[35]	256 × 256 126 cases	T1 w, T2 w, and Flair	126 Subjects
Harvard[34]	256 × 256 (100 images)	T2 w	65 tumor and 35 non-tumor images

TABLE 4. Summary of brats datasets from the year 2012 to 2021.

Year	Time point	Tasks	Data				Type of MRI
			Total	Training	Validation	Testing	
2012	preoperative	Segmentation	50	35	Not available	15	Multi contrast MRI
2013	preoperative	Segmentation	60	35	Not available	25	Multispectral
2014	Longitudinal	Segmentation	238	200	Not available	38	T1, T1c, T2, FLAIR
2015	Longitudinal	Segmentation and disease progression	253	200	Not available	53	
2016	Longitudinal	Segmentation and disease progression	391	200	Not available	191	
2017	preoperative	Segmentation and survival prediction	477	285	46	146	
2018	preoperative	Segmentation and survival prediction	542	285	66	191	
2019	preoperative	Segmentation and survival prediction	626	335	125	166	
2020	preoperative	Segmentation and survival prediction	660	369	125	166	
2021	preoperative	Segmentation and classification	2040	1251	219	570	

V. CNN BASED SEGMENTATION

The clinical applicability of the T1w MRI sequence for tumor segmentation has been improved by the cross-modal distillation approach to train the convolutional neural network (CNN) with multi-MRI sequences such as T1w, T1c, T2w and FLAIR [69]. The high and low grades of glioma tumor were segmented by introducing three types of architectures based on CNN [70] namely Sparse Multi OCM, Input Sparse Multi OCM and Dense Multi OCM using Occipito-temporal pathway technique. The authors also used overlapping patches to extract both local and global features. A network architecture, DRINet [71] has been proposed based on the architectures of Dense Net [72], [73] for analysis and Residual Inception Net [74] for synthesis without pooling. In order to overcome the convergence problems in the convolutional neural network (CNN), recently, some researchers focused on quantum

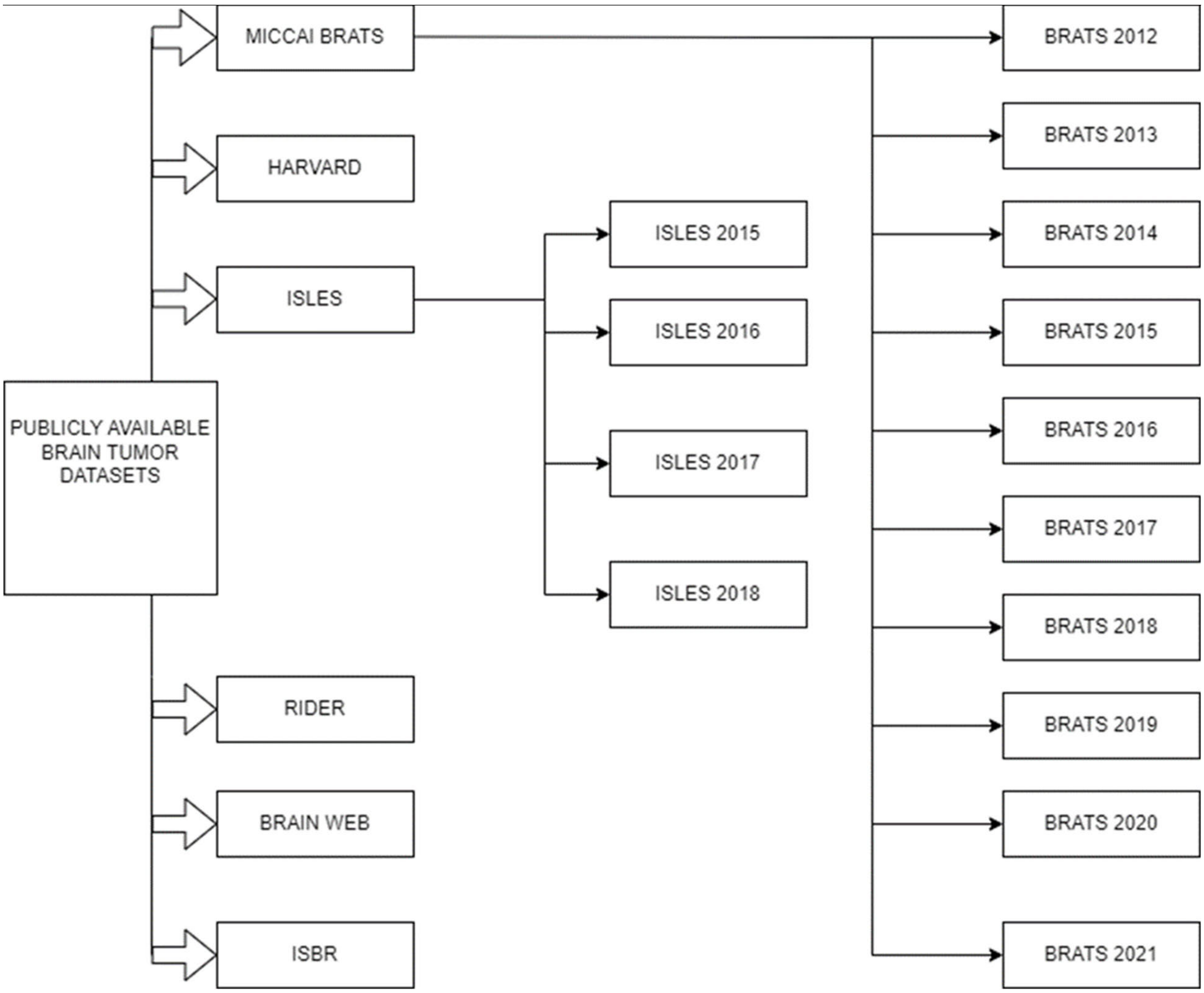

FIGURE 5. Publicly available dataset.

neural networks. A quantum network with new architecture has been proposed in [75] for the automatic segmentation in which the pixel intensity of the image was considered as the quantum bits and the weight of the intermediate layer for each neuron was set as $\pi/2$ wherein the input layers were the gated layer and multiclass quantum inspired sigmoidal function was used.

The architecture proposed in [75] was replicated in [76] with some functional modification in the quantum inspired sigmoidal function. The Otsu's scheme has been emphasized to optimize the architecture proposed in [77] by maximizing the variance of classes in the case of multiclass level classification. A new network was proposed using the basis of qutrit of quantum computing [78] for the counter propagation with self-supervising to update the weights of the intermediate layer. But the methods proposed in [75], [76], [77], and [78] dealt only with the T1c modality of MRI images. The local and contextual information were extracted from the MRI image [80] by hybridization of two-path and three path networks [79] to detect the brain tumor. The brain tumor part was segmented from the fused version of CT, MRI, PET and SPECT images using robust edge analysis and probabilistic neural network [81].

Brain tumor part was segmented using heterogeneous CNN from the three planes of MRI images and optimized by conditional Radom fields based recurrent regression neural network [82]. The segmentation was achieved by aggregating the results of two different CNNs [83] wherein one CNN used 2 convolutions at each layer and another one used 3 convolutions at each layer. The tumor segmentation was enhanced by reducing the effect of overlapping image patches [84] by introducing conditional Random Fields, a kind of CNN. The network architectures exclusively for whole tumor detection, tumor core detection and enhanced tumor were cascaded to frame a new architecture called CA-CNN [85] and used in [86] from the four modalities of brain tumors. The Bat algorithm and the improved invasive Weed Optimization were combined with the Residual network [87] to improve

TABLE 5. Summary of tumor types with publicly available brain tumor dataset.

Work	Dataset	Tumor Types
[39][40][41] [42][43]	FIGSHARE	GLIOMA MENINGIOMA PITUITARY
[44][45][42][43]	REMBRANDT	ASTROCYTOMA GLIOBLASTOMA OLIGODENDROGLIOMA
[37]	TCIA	GLIOMA
[38][46]	REMBRANDT	LGG HGG
[47]	TCGA-GBM	GLIOBLASTOMA MULTIFORM
[48][46]	TCGA-LGG	LGG
[33][49]	IXI Dataset	NORMAL
[46]	RIDER	GLIOBLASTOMA
[50]	BraTS 2012-2016	NECROSIS EDEMA NON ENHANCING TUMOR ENHANCING TUMOR
[51] [52][53]	BraTS 2017-BraTS2021	LGG HGG

the tumor segmentation using multimodal MRI images. However, the performance of the quantum neural network and its types are slightly lower than the CNN based Neural Networks [69], [88], [89], [90], [91], [92], [93], [94], [95], [96]. The CNN based architecture proposed in [95] is depicted in Fig.6 wherein T1 and T2 images are fused.

VI. U-NET BASED SEGMENTATION OF BRAIN TUMOR

In the literature, the researchers have attempted to segment the tumor part by utilizing the advantages of four modalities of MRI brain images using a kind of deep architecture called U-Net.

A. NETWORK ARCHITECTURE OF U-NET - BASICS

The functional structure of basic U-Net [97] is illustrated in Fig. 7. In this basic structure, there are two phases namely 1) encoder and 2) decoder may also be called respectively as 1) down-sampling and 2) up-sampling. Usually, in U-Net architecture, four stage convolution on the encoder side and three stage convolution on the decoder side is performed. The purpose of the encoder is mainly for size downing the image.

In Fig. 6, the 572 $\times$ 572-dimensional original image is taken and the same is reduced (down sampled) by the encoder at each stage. Using a decoder (up -sampling), the reduced image size is resumed to its original size. In the existing works, a pooling layer may be used to reduce the unwanted features. The basic difference between the CNN architecture and the U-Net architecture is the concatenation of features of encoder and decoder. The CNN architectures perform only the segmentation whereas U-Net architectures can perform image fusion, segmentation and fused segmentation. And hence, this study focuses more on U-Net based architectures.

B. U-NET BASED SEGMENTATION OF BRAIN TUMOR

The fusion of T1c, T2 and FLAIR MRI sequences has been achieved using a deep network called SF-Net [88] wherein the fusion, an auxiliary task of the network was used to advance the segmentation accuracy. This network achieved segmentation accuracy higher than an asymmetrical U-Net with a variational auto encoder branch [98]. A two stage cascaded U-net proposed as a variant of this approach [99]. The authors dynamically adjusted the loss weights based on an uncertainty approach [89] instead of a static adjustment. The high informative patterns of brain tumor were extracted from the different modality of MRI sequences to train the network and transferred them to one modality using a generative adversarial network for improved tumor segmentation [90]. A new framework called KD-Net was introduced in [91] to train the network with a multimodality MRI sequence (teacher model) to enhance the accuracy of segmentation using a T1c MRI sequence (student model). A U-Net [92]

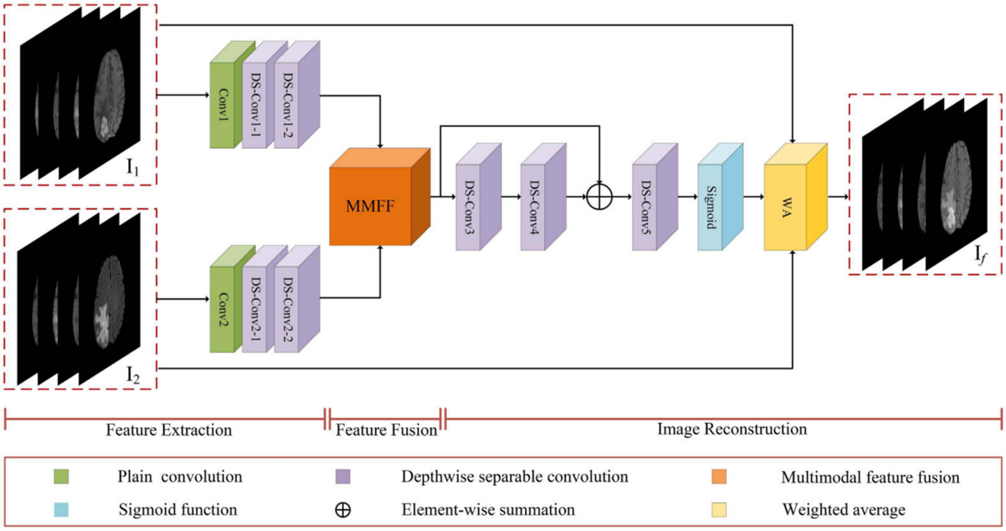

FIGURE 6. Architecture proposed in [95].

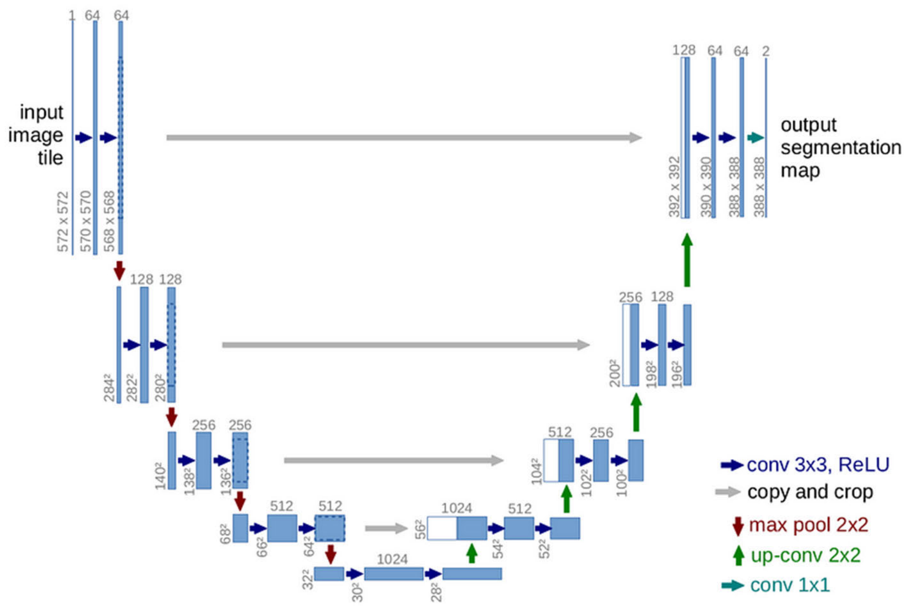

FIGURE 7. Network architecture of basic U-Net [97].

based correlation model has been proposed [93] wherein the features of each modality were extracted by separate encoders for discovering the correlation between them to get the fused representation. From the fused representation, the enhanced version of each modality and segmentation of tumor were obtained using separate decoders. The fusion of volumetric multimodal MRI data was achieved using depth wise separable convolution [94] from the fused features of multimodal MRI sequences [95]. The features of four modalities of MRI images were obtained using a dual network [96] in which the fused features of tumor and modality specific feature codes were decoupled to tumor specific features. Then the features were reconstructed to get the segmented image of the brain tumor.

A hierarchical fusion strategy [100] was employed in U-Net to fuse the features from the encoder and the skip function using a hybrid fusion network. In this work, images of each modality of MRI were given to individual encoders with an atrous convolution and the hybrid attentional fusion was applied to fuse the features of multiple modality images. Hence this network required only one decoder to get the segmented image. Fine grained, multi scale and long dependent glioma features were obtained using auto-weight dilated convolution [101] instead of normal convolution for the fusion of multimodal MRI images and to segment the tumor regions.

The advantages of deep learning based segmentation and statistical based segmentation were integrated [102] to refine the segmentation using MRI images. A U-Net of U-Net [103] has been proposed in which U-Nets were embedded in the up sampling part and four ResNet in the down sampling part and also, the brain tumor segmentation was achieved by serial and parallel merging the output of each ResNet with the corresponding U-Net. The U-Net has been modified using the inception module in each layer in [104]. The inception module was designed by the concatenation of two serially connected 3×3 convolutional kernels, one 5×5 kernel and one 1×1 kernel in both stages of sampling of the U-Net. Three variants of a lightweight hierarchical convolutional network were constructed [105] using a residual hierarchical convolutional network for fusing the advantages of MRI images of T1c, T2 and FLAIR for segmentation.

The U-Net architecture was modified in [106] by the integration of many parallel convolutions with pooling in the down sampling part and aggregation of features obtained from convolution at each layer in up sampling part with the corresponding down sampling part for segmentation of tumor using the masked four types of MRI brain images. The author proposed a transformer based segmentation approach called UNETR [107] in which a transformer encoder connects directly to decoder via skip connection for medical image segmentation.The U-Net was combined with a dual encoder based R –Transformer network in [108] which constituted a feature branch for extracting global context information and a patch branch for extracting semantic features from the different modalities of MRI images. A new network named Z-Net [109] was proposed with single convolution layers at the beginning of the down sampling part and end of the up sampling part and double convolution at all other layers to segment the brain tumor in binary version.

A $1 \times 1 \times 1$ convolution was performed after a $3 \times 3 \times 3$ convolution for depth wise separable convolution [110] at each stage in U-Net to segment the tumor from all modalities MRI images. Brain tumor has been segmented using an MRI brain image and its edge image by a modified U-Net architecture called Edge U-Net [111] wherein the edge guidance block obtained from the image and its edges in down sampling were concatenated with the concerned-up sampling part. The U-Net architecture was also modified with efficient spatial attention (ESA) [112] block with depth-wise separable convolution and lightweight spatial attention module instead of conventional convolution to segment the tumor in MRI FLAIR brain images. A new block called context block [113] has been introduced between the encoder and decoder part to aggregate the contextual multi scale information. The accuracy of the segmentation of tumor sub region has been increased using the application of context block.

A U-Net based neural network has been introduced in [114] by connecting a deep network and an auxiliary network. The coalescing convolution was applied at the deep network to gather the highlighted tumor region and then the same was given to the auxiliary network with different modalities of MRI brain images. An approach of generalized pooling [115] by unifying the average pooling and maximum pooling was introduced and tested in U-Net. The study concluded that the generalized pooling have increased the accuracy of segmentation of WT, TC and ET. A 3-D U-Net architecture modified with lightweight variant architecture called HDC – Net [116], a computationally more efficient one was presented to decrease the number of channels to segment all tumor sub regions in one pass.

Fig.8 and Fig.9 depict the architecture developed in [88] and [93] respectively. Both [88] and [93] provide fused and segmented images. An improved U-Net architecture called InR-ResCBAM-U-net [117] was used for simplified training of DNN to achieve segmentation with higher accuracy. A CNN with U-Net based model was proposed in [118] to rectify the problem of tumor segmentation and the brain tumor was classified as non-enhancing tumor, necrosis, enhancing tumor and edema. The performance of the developed models based on U-Net for segmentation of abnormalities in brain using MRI images was compared by different learning parameters [119]. In this FLAIR MRI scan was used for the segmentation of WT, TC and ET. The difference between the variants of U-Net architectures proposed in [69], [88], [93], [98], [99], [100], [101], [103], [106], [108], [109], [110], [111], [112], [116], and [117] are summarized in Table 5. The U-Net architecture was modified by hybridizing the network [120] with residual block and attention block (in between the concatenation of down sampling part with up sampling part) and deep supervision block at the end of the decoder part from multi-resolution T1c, T2 and FLAIR MRI images. The tumor was segmented using three U-Net with three planes of MRI brain images and then majority voting was applied to select the best segmented results [121]. A hybrid architecture resembling the U- Net was introduced with DenseNet121 in the encoder part and U- Net in the decoder part for tumor segmentation using MRI images [122].

The U-Net was also modified [123] with ResNet-50 [124] in the encoder part and the squeeze and excitation network [125] in the decoder part. A U-shaped weight alignment module [126] was proposed by hybridization of the residual module and multi-channel multi-scale module to extract the targeted information using dilated attention module. The tumor part in brain image was segmented with the maximum features using the ensemble of the segmented image obtained from an auto encoder, SEGNet and U-Net [127]. Masked manual segmented brain tumor images were combined with the concerned enhanced images for the accurate segmentation of glioma using U-Net [128]. Also, in this work, grade II and grade-III glioma were classified using VGG16.

The types of brain tumors (here three) were segmented from enhanced version of MRI images by Fuzzy logics using DeepBrainet2.0 [129] which was optimized by varying the

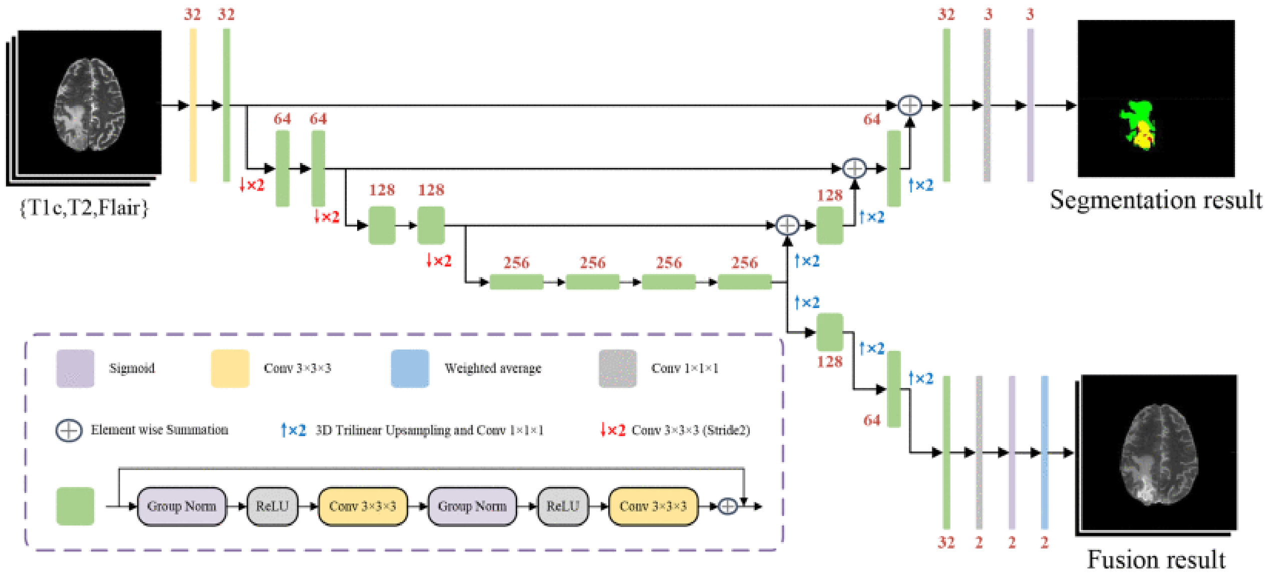

FIGURE 8. Architecture of SF-Net proposed in [88].

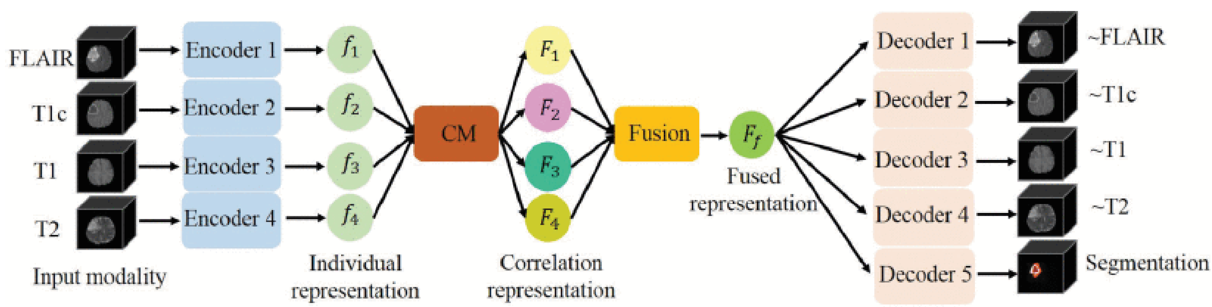

FIGURE 9. Architecture proposed in [93].

number of both neurons and layers of the architecture. A new type of U-Net called DDU-Net was proposed in [130] with single encoder and dual decoder for extracting edge features and semantic features and were fused to obtain segmented tumor image. The tumor segmentation was performed using 3D U-Net and from this segmented image, the intra tumor features were extracted using a local symmetric inter sign operator [131] using U-Net. Transformer based U-Net architecture was proposed to utilize the advantages of PSWin [132] transformer with U-Net for tumor segmentation. Also, U-Net architecture was modified by a structure called up-skip connection [133] in which weighted the addition of two continuous down sampling parts with the concerned-up sampling part to enhance the segmentation of brain tumor. A new architecture called CANet [134] has been introduced to get the fused image of brain tumor from three segmented brain tumor images obtained from the four modalities of MRI images. A new architecture called RD2A-SPP [135] was modelled in which the atrous spatial pyramid pooling was introduced to segment the brain tumor part from MRI images. The fusion of MRI and Computed Tomography (CT) images of brain tumor was performed [136] using 2D and 3D U-Net Architectures to register and segment the tumor part. A new network architecture was developed based on Deeplabv3+ [137] in which the ResNet 18 was utilized in the down sampling part and dilated convolution with ASPP were used between the encoder and decoder parts to segment the tumor part for classification. The conventional U-Net was modified [138] with three variants of ResNet-50, ResNet-101 and ResNet 50 in the down sampling part to extract the multi- channel feature maps to segment the brain tumor from MRI images. The summary of variants of U-Net Architecture is depicted in Table5.

For medical image segmentation, Zhou et al. [139] suggested a variant of the U-Net model called U-Net + +, with nested structure and re-designed skip connections. This model worked well for image segmentation from electron microscopy (EM), CT, MRI, and histopathology. The U-Net++ [140] architecture is illustrated in Fig. 10. U-Net++ is a network that uses dense convolutional blocks to bridge semantic gaps between encoder and decoder feature maps. The original U-Net is shown in black in the graphical abstract, dense convolution blocks on the skip paths are

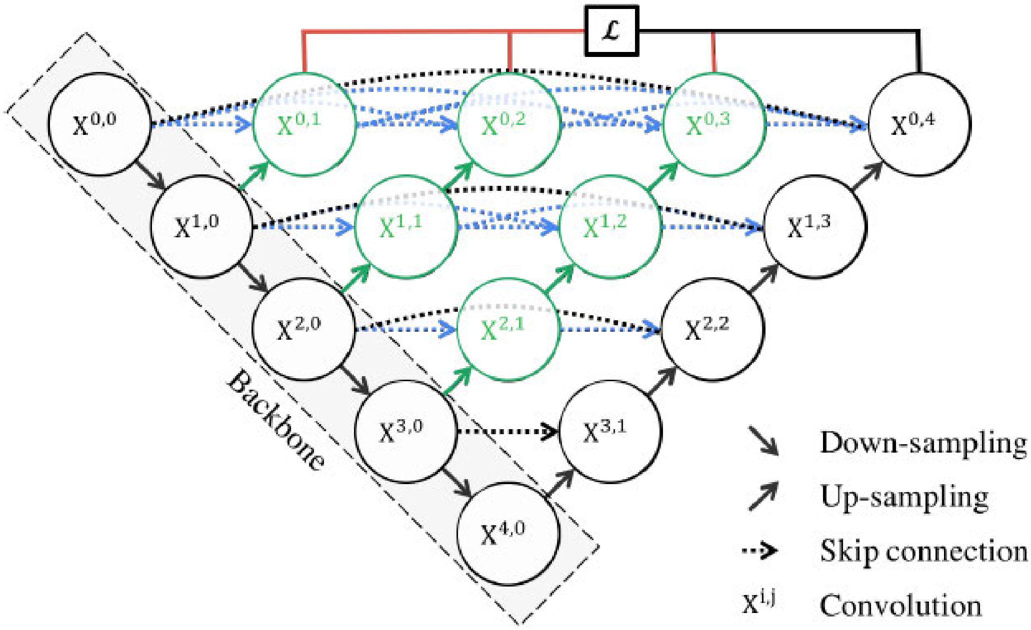

FIGURE 10. Architecture proposed in [140].

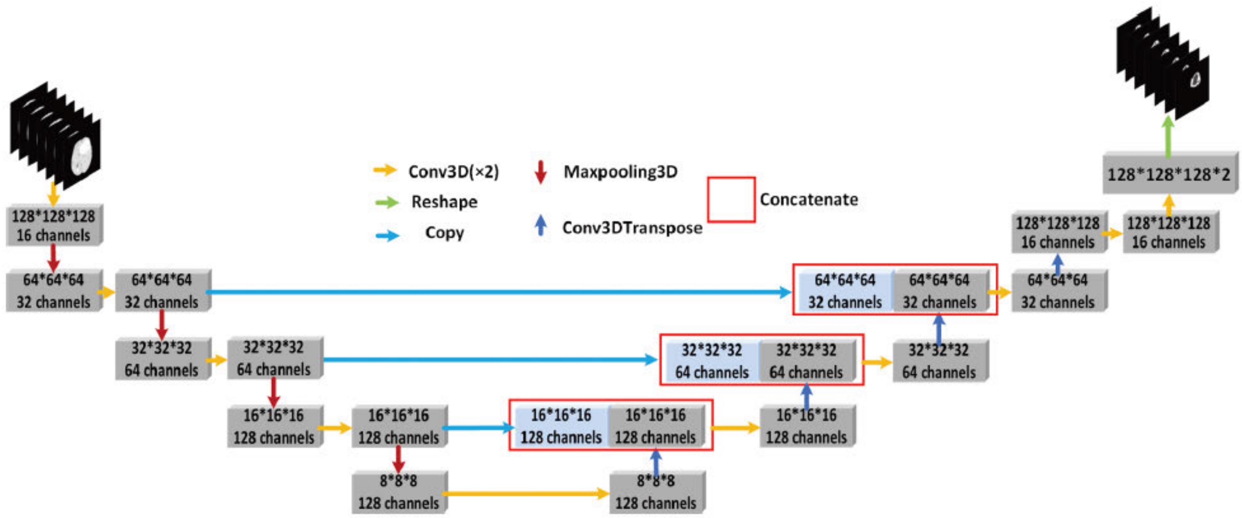

FIGURE 11. 3D U-Net architecture proposed in [144].

shown in green and blue, and deep supervision is shown in red. U-Net++ is distinguished from U-Net by its red, green, and blue components In [141] the accuracy of brain tumor segmentation improved further by introducing multi-scale jumping connection. In [142] introduced a multimodal brain tumor segmentation model called DenseTrans model that combines enhanced Swin Transformer and U-Net++. The model extracts local features using the enhanced U-Net++ Encoder. Each layer in the hierarchical U-Net then sends the extracted features to the swin transformer, which learns the long-distance dependency and retrieves the global context data. In [143] author improved segmentation accuracy by optimization of inception v2 net by segmentation net with 16 new layers for whole tumor detection and FFCM used for tumor core and edema detection. Li et al. proposed a cascaded 3D U-Net and 3D U-Net++ [144] in which two 3D U-Net for whole tumor and tumor core segmentation and 3D U-Net++ for enhanced tumor segmentation effectively. Fig.11 and Fig.12 depict the architectures developed in [144]. In [145] author proposed a two stage transfer learning approach comprised of U-net with residual network for brain tumor detection and YOLO2 for classification of glioma, meningioma and pituitary tumors. The author proposed an optimized U-net [146] for brain tumor segmentation after

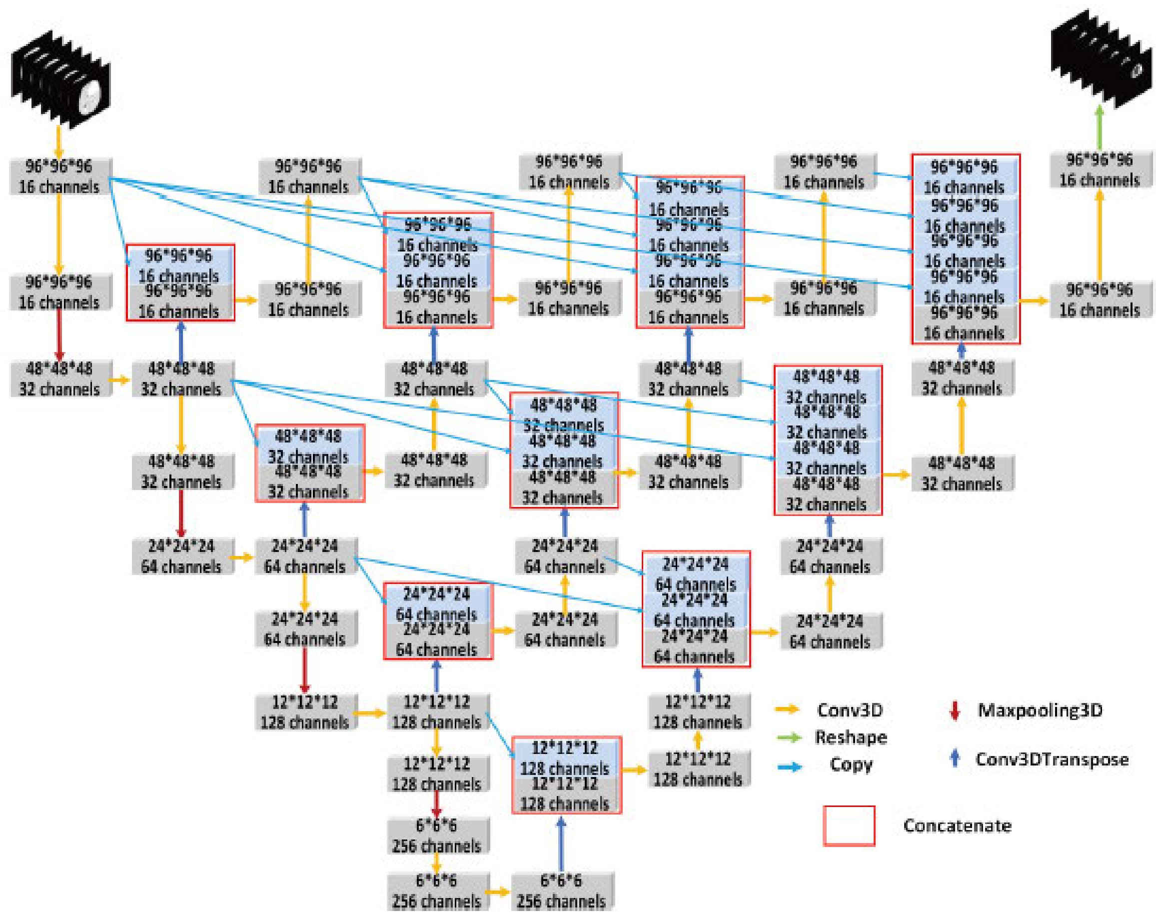

FIGURE 12. 3D U-Net++architecture proposed in [144].

experimenting different U-net variants-UNETR [107], Seg-ResNetVAE [98], Residual U-Net [147], and Attention U-Net [148]). The summary of variants of U-Net Architecture is depicted in Table 5.

VII. PERFORMANCE EVALUATION

In the literature, most of the researchers used the dice similarity coefficient (Dice Score) and the 95 percentile Hausdorff distance (95% HD) to evaluate the performance of the segmentation of the brain tumor using MRI images.

A. DICE SCORE

The overlapping between the annotations and the performed segmentation is the Dice score [149] and is given by

$$Dice = \frac{2\,|a \cap b|}{|a| + |b|}$$

where a is the foreground voxel set in annotation and b is the foreground voxel set in the performed segmentation.

B. HAUSDORFF DISTANCE (95%)

The maximum distance between a set and the nearest point of another set is called maximum Hausdorff distance [149]. Let X and Y be two different sets as in Fig. 13.

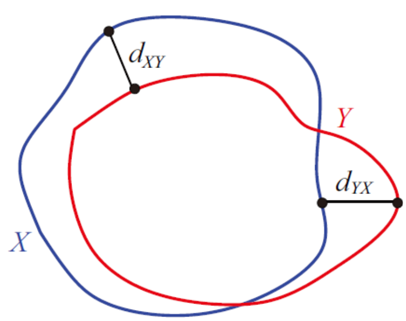

FIGURE 13. Hausdorff distance estimation curve.

The Hausdorff distance from set X to set Y is a maximum function given by

$$d_H\,(X, Y) = \max\,(d_{XY}, d_{YX})$$

The measured values of Dice score and Hausdroff distance (Hd95) by the methods [88], [93], [98], [99], [101], [103],

TABLE 6. Summary of comparison of variants of U-NET architecture.

Work	Architecture	Datasets	Task
[98]	Asymmetrical U-net with variational autoencoder	BraTS 2018	Segmentation
[99]	Two stage cascaded U-net	BraTS 2019	Segmentation
[88]	Dual Up sampling	BraTS 2020	Segmentation + Fusion
[93]	4 Encoder + 5 Decoder	BraTS 2018, 2019	Fusion + Segmentation
[100]	Dual Encoder	BraTS 2019	Fusion + Segmentation
[101]	Auto weight dilated convolution	BraTS 2020	Fusion + Segmentation
[108]	R-Transformer Net with dual Encoder	BraTS 2017	Fusion + Segmentation
[69]	Cross Modal Knowledge Distillation and Cross Modal Feature Fusion	BraTS 2018	Segmentation
[103]	ResNet at Encoder and U-Net at Decoder	BraTS 2017, 2018	Segmentation
[106]	Integration of convolution	BraTS 2018	Segmentation
[110]	Attention module in decoder	BraTS 2020	Segmentation
[112]	Efficient Spatial Attention Block	BraTS 2021	Segmentation
[116]	Hierarchical Decoupled convolution	BraTS 2017, 2018	Segmentation
[117]	Residual Convolution Block Attention Module	BraTS 2019	Segmentation
[127]	Autoencoder -decoder, SEGNET, U-Net	BraTS 2017	Fusion + Segmentation
[126]	Hybrid weight alignment Multi dilated attention	BraTS 2017	Fusion + Segmentation
[134]	Context encoding between encoder and decoder	BraTS 2019	Segmentation + Fusion
[120]	Hybrid U-Net with Multiresolution, dual attention and deep supervision	BraTS 2020	Binary Segmentation
[121]	Three views of MRI with 2D U-Net and Majority voting	BraTS 2019	Segmentation
[122]	Hybrid DenseNet121 based U-Net	BraTS 2019	Segmentation
[123]	ResNet50 at encoder and Squeeze and Excitation at decoder	BraTS 2018, 2019	Segmentation
[130]	Dual decoder – edge prediction and segmentation	BraTS 2017, 2018	Segmentation
[132]	3D PSwin Transformer with Semantic Attention	BraTS 2020, 2021	Segmentation
[133]	Inception based U-Net Up skip connection between encoder and decoder	BraTS 2015, 2017	Segmentation
[135]	Residual dilated dense atrous spatial pyramid pooling	BraTS 2018, 2019	Segmentation
[138]	ResNet/ResNext	Figshare	Segmentation
[131]	3D U-Net for tumor segmentation and 2D U-Net for intratumor segmentation	BraTS 2015	Intratumor Segmentation
[143]	Inceptionv2 Net +Segnet,FFCM	BraTS 2017, 2020	Segmentation
[145]	U-Net with Residual network	Figshare	Segmentation
[139]	U-Net++ with nested structure and redesigned skip connection	BraTS 2013	Segmentation
[141]	U-Net++ with multi scale jump connection	BraTS 2018, 2019	Segmentation
[142]	Improved U-Net++ and swin transformer	BraTS 2021, 2020	Segmentation
[144]	Cascading structure of two 3D U-Net and one 3D U-Net++	BraTS 2019	Segmentation + Fusion

[106], [108], [110], [112], [116], [117], [120], [121], [122], [123], [126], [130], [131], [132], [133], [134], [135], and [144] are extracted in Table 7.

From the values in Table 7, it is inferred that the methods which used the BraTS dataset 2019 outperformed compared to other datasets in terms of Dice Score and Hd95. Even though the BraTS 2020 and BraTS 2021 datasets have more information compared to BraTS 2019, the performance of the methods is not satisfactory. The performance of segmentation of ET is poor compared to TC and WT irrespective of methods and datasets.

VIII. BRAIN TUMOR SEGMENTATION CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Brain tumor segmentation faces several challenges, including variability in tumor appearance, image quality, inter-observer

TABLE 7. Measured values of dice score and Hd95.

Performance →		Dice Score			Hausdroff Distance (Hd95)		
Ref	Dataset	WT	TC	ET	WT	TC	ET
[112]	BraTS 2021	0.91	0.85	0.81	5.94	13.83	26.47
[132]		0.93	0.87	0.83	3.74	11.08	17.53
[88]	BraTS 2020	0.89	0.83	0.81	7.10	6.44	3.89
[101]		0.90	0.80	0.76	7.22	15.3	35.2
[110]		0.90	0.83	0.77	5.61	7.10	25.07
[120]		0.75	0.62	0.60	11.05	22.5	46.84
[132]		0.91	0.84	0.79	5.57	7.25	19.44
[93]	BraTS 2019	0.87	0.72	0.73	6.7	9.3	6.3
[144]		0.87	0.83	0.80	Not Available		
[117]		0.90	0.88	0.84	2.54	1.61	2.62
[121]		0.90	0.84	0.77	5.12	3.89	3.05
[122]		0.96	0.94	0.89	Not Available		
[123]		0.94	0.92	0.88	2.15	1.37	2.32
[99]		0.89	0.84	0.83	4.62	4.13	2.65
[134]		0.89	0.84	0.82	4.89	6.71	3.32
[135]		0.90	0.82	0.72	4.69	7.09	3.32
[93]	BraTS 2018	0.8	0.78	0.71	6.5	9.9	7.1
[98]		0.88	0.82	0.77	5.9	4.8	3.77
[103]		0.85	0.93	0.79	Not Available		
[106]		0.99	0.92	0.90	5.00	4.24	4.46
[116]		0.89	0.84	0.82	4.59	8.76	2.42
[123]		0.94	0.92	0.87	2.13	1.28	2.10
[130]		0.89	0.84	0.78	5.92	6.56	4.40
[135]		0.9	0.84	0.78			
[103]	BraTS 2017	0.81	0.91	0.75	5.92	6.56	4.40
[108]		0.83	0.78	0.73	5.3	4.6	5.5
[116]		0.90	0.81	0.76	Not Available		
[126]		0.89	0.76	0.68	26.70	19.94	17.41
[131]		0.89	0.84	0.78	5.92	6.56	4.40
[133]		0.88	0.76	0.64	Not Available		

variability, tumor heterogeneity, partial volume effect, data imbalance, registration and motion artifacts, edema and infiltration, computational complexity, lack of annotated data, generalization across scanners and acquisition protocols, and real-time clinical use. To address these challenges, researchers can develop robust algorithms [150], [151], [152] using deep learning techniques like convolutional neural networks (CNNs), improve image quality through preprocessing techniques, create standardized annotation protocols, employ advanced models like 3D CNNs or multi-modal imaging data, and consider local image information to accurately distinguish tumor boundaries. Data imbalance can be mitigated by using techniques like oversampling, under sampling, or class weighting during training. Image registration techniques can correct for motion artifacts and ensure alignment between multi-modal images, improving the accuracy of segmentation across different modalities and time points. Advanced segmentation algorithms can distinguish between the tumor core and surrounding edema or infiltrative regions, incorporating features such as intensity, texture, and shape. Computational complexity can be optimized by using parallel processing, hardware acceleration, and cloud computing resources, as well as real-time implementations or accelerated model architectures for clinical use. Collaborating with medical institutions to create large, diverse, and well-annotated datasets can increase the effective size of the dataset and improve model generalization. Domain adaptation techniques or transfer learning approaches can make models more robust to variations in imaging equipment and protocols. Real-time processing can assist in clinical decision-making during surgery or treatment planning. In conclusion, collaboration between computer scientists, radiologists, and healthcare professionals is essential for developing effective tools for brain tumor segmentation that can improve patient care and outcomes.

To achieve robust and reliable segmentation methods with deep learning, challenges include long training times, over-fitting, and vanishing gradients [153]. Batch normalization [154], [155] is used to address these issues, while overfitting [156] occurs when the number of images in the target domain is small. Techniques like augmentation [157] can increase the number of data. Vanishing gradients [158] are a major issue in deeper networks, as the final loss value may not be efficiently back-propagated into shallow layers. Several algorithms [159], [160] have been proposed to combat these issues. Research on brain tumor segmentation primarily relies on fully supervised methods, which are time-consuming and labour-intensive. Recent studies have evaluated self-supervised representations, and future methods are expected to use self, weak, and semi-supervised training with fewer labels.

Deep learning in brain tumor segmentation is a rapidly evolving field that requires further development. Future directions include improving model generalization, incorporating new technologies, and expanding the scope of applications. These include developing models that can perform well on diverse datasets and clinical scenarios, enhancing transfer learning and domain adaptation techniques, developing interpretable and explainable models, integrating information from multiple imaging modalities, and developing efficient 3D image segmentation models. Clinical integration and validation are also crucial, with large-scale, multicenter studies being conducted to validate deep learning models in real-world clinical settings. Real-time and edge computing environments can facilitate the integration of deep learning models into clinical workflows, and future work may explore optimizing models for efficient deployment on resource-constrained platforms. Addressing concerns related to patient data privacy and security is also crucial for the adoption of deep learning models in healthcare. The integration of information from multiple imaging modalities, such as MRI, CT, PET, and functional imaging, can provide a more comprehensive understanding of tumor characteristics. Future research could explore methods for fusing data from diverse sources to improve segmentation accuracy. Weakly supervised learning techniques can be used to address limited annotated data, while transfer learning and domain adaptation techniques can generalize models to different imaging conditions, populations, and institutions. Explainable AI (XAI) is essential for enhancing transparency and clinical acceptance of deep learning models. Incorporating dynamic and functional imaging data, such as perfusion or diffusion-weighted imaging, could provide valuable insights into the tumor's physiological properties. Automated lesion grading and characterization could provide clinicians with additional information for treatment planning and prognosis. Uncertainty quantification is essential for clinical decision-making, and future research might explore methods for uncertainty quantification in brain tumor segmentation. Collaborative learning approaches, where models are trained across multiple institutions without sharing raw data, can address privacy concerns. Federated learning techniques can enable collaborative training of deep learning models on decentralized datasets. Interactive and real-time segmentation could improve the usability of deep learning tools. Ethical considerations and bias mitigation are crucial as AI technologies are integrated into healthcare. Large-scale clinical validation studies and integration of deep learning models into routine clinical workflows are essential steps for real-world impact. These directions reflect the evolving nature of deep learning research in brain tumor segmentation.

IX. CONCLUSION

Thus, the state-of-the-art works for the segmentation of brain tumor using MRI images are analyzed and their performances are compared. The architecture of various CNN based and DNN based neural networks have been surveyed. Further, the benchmark datasets released from 2012 to 2021 and other publicly available datasets were discussed. Based on this survey, it can be concluded that the U-Net based architecture of DNN outperformed well compared to CNN based segmentation and the conventional segmentation methods. Also, we suggest that the performance of the brain tumor segmentation can be improved by using a large sized dataset for training with implementing modifications in the U-Net architecture for reducing the computational complexity.

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R. PREETHA received the B.Tech. degree in electronics and communication engineering from M. G. University, Kottayam, Kerala, India, in 2009, and the M.E. degree in applied electronics from Anna University, Chennai, Tamil Nadu, India, in 2013. She is currently pursuing the Ph.D. degree with the Vellore Institute of Technology. Her area of research is digital image processing.

M. JASMINE PEMEENA PRIYADARSINI received the B.E. degree in electronics and communication engineering from the University of Madras, Chennai, Tamil Nadu, India, in 1992, the M.E. degree in microwave and optical communication from Madurai Kamaraj University, Madurai, Tamil Nadu, in 1995, and the Ph.D. degree from the Vellore Institute of Technology, Vellore, Tamil Nadu, in 2016. Currently, she is a Professor and the Associate Dean with the School of Electronics Engineering, Vellore Institute of Technology. Her area of research interests include digital signal and image processing, wireless communication, applied electronics, and optical image processing.

J. S. NISHA received the B.E. degree in electronics and communication engineering from the University College of Engineering, Kariyavattom, the M.E. degree in signal processing from the College of Engineering Trivandrum, India, and the Ph.D. degree from the National Institute of Technology, Tiruchirappalli, India. Currently, she is an Assistant Professor (Grade 1) with the Department of Sensor and Biomedical Technology, School of Electronics Engineering, Vellore Institute of Technology, Vellore. Her research interests are in the areas of medical image processing, machine learning, and deep learning. More specifically, cancer detection from colonoscopy images.