A Short Review on the Role of Various Deep Learning Techniques for Segmenting and Classifying Brain Tumours from MRI Images

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***Abstract*—The past few years have observed substantial growth in death rates associated with brain tumors and it is second foremost source of cancer-related demises. However, it is possible to increase the chance of survival if tumors are identified during initial stage by employing various deep learning techniques. These techniques are helpful to the doctors during the diagnosis process. The MRI which refers to magnetic resonance imaging is a non-invasive procedure and low ionization radiation diagnostic tool to evaluate an abnormity that evolves in the form of shape, location or position, size and texture of tumour. This paper focuses on the systematic literature survey of numerous Deep-Learning methods with suitable approaches for tumour segmentation and classification (normal or abnormal) from MRI images. Furthermore, this paper also provides the new aspects of research and clinical solution for brain tumor patients. It incorporates Deep-Learning applications for accurate tumor detection and quantitative investigation of different tumor segmentation techniques.**

Keywords*—*Medical image segmentation; convolutional neural networks (CNN); deep-CNN; feed forward neural networks; brain tumor segmentation (BraTS) and U-net

I. Introduction

Brain tumors are neurological fatal disorders, a bunch of atypical cells that are found increasing in the human brain or by the surroundings of the brain that which affects the normal brain cells and further results in cancer [1]. They are classified into two variants malignant, which is cancer causing and benign which is non-cancerous. Benign tumours are less offensive, form gradually and are isolated from normal tissues regularly. Malignant tumors develop quickly, lack of defined boundaries, and are difficult to identify from normal tissues [1, 2]. These tumors cause more pain inside the brain and can migrate to the spinal cord. At the same time, malignant tumors are complex to eliminate entirely from the cells in the brain; moreover these tumours have tendency to transform to cancer which is deadly. The second prime reason for most cancer related deaths is the malignant kind of brain tumour [3].

As per statistics, there are approximately 12.7 million cancerous persons in the world each year, with 7.6 million people dying because of cancer [4]. The Hindu published an article in 2016 that reported that around 2,500 children of India suffered from malignant tumors every year and every year 20% of children were diagnosed with brain tumors if 4,000 to 5000 people were diagnosed [4, 5]. Conferring to the American Brain Tumor Association (ABTA), about 78,000 new brain tumour cases will be diagnosed by year end of 2018. According to a poll conducted by the "Times of India," approximately three million individuals in India suffer from cancer, with one million being diagnosed with new kinds of cancer. As stated by the "WHO" (World Health Organization) one-third of brain tumours are cancerous [1-4]. As stated by the "UNI" (United News of India) brain tumours are the tenth most prevalent tumor in India. As per doctors' point of view, 90% of brain tumor cases can cure and may save many lives when detecting the brain tumor at an early stage. Hence early detection of brain tumors can increase the chance of survival [2-4].

The manual analysis of MRI reports of human brain are utilized in finding the exact boundaries of the tumors by physicians which is an intricate and demanding task Not only because of little brightness and contrast of MRI reports but also similarities of intensities among brain organelles [6]. The physical evaluation tissues of brain membrane requires ample knowledge and time-overwhelming tasks to diagnose the patient. As per the "MOHFW" (Ministry of health and Family Welfare-Government of India), there is no specific reason for brain tumors, and the possible survival rate is less than 3%. All these issues motivated the author to investigate the different automated brain tumor segmentation techniques and suitable methods to reduce the mortality rate [4-6].

In this survey, the researchers have deliberated recent and popular state of the art Deep-Learning techniques not only to segregate the variants of tumours that affect brain but also to categorize the kinds of brain tumours including Machine Learning Techniques (MLT), Artificial Intelligence (AI), and Deep-learning techniques.

Among various modalities (CT, US, and PET), the MRI modality supports the identification of brain tumors by radiologists due to low ionization and noise. To soft brain tissues MRI is more appropriate and envisages the anatomy of the brain in three different planes such as axial, sagittal, axial, and coronal view [6, 7]. Fig. 1 shows the axial, sagittal, and coronal views of the brain captured using the MRI modality or imaging technique.

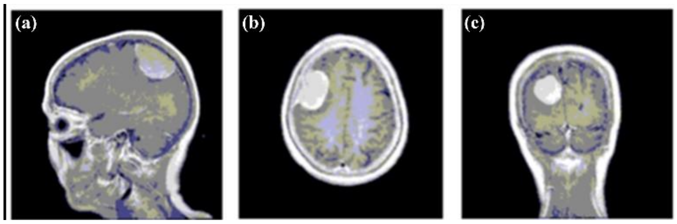

Fig. 1. Brain MRI Slices Captured from Different Directions (a) Sagittal, (b) Axial, and (c) Coronal.

MRI has various benefits over other imaging techniques, including i) high spatial resolution, ii) Functional brain measurement, iii) MRI test is acceptable for patients of any age, iv) No harmful effects on the body (no risks) due to no ionizing radiation effect, and iv) It can take images in any plan and capture finer details of soft tissues [8].

Today most of the research workout on machine learning algorithms intended to segregate the variants of tumors that affect brain automatically having capability, accuracy, reproducibility, scalability, and ease of a quantitative estimation of brain tumors [7, 9].

The methods are classified as Deep learning and Machine Learning methods. Traditional MLT use statistical learning approaches and better classify the features of low-level brain tumor. These learning methods concentrated on the estimation and localization of boundaries of the tumor [10]. The deep learning methods are requiring the smallest pre-processing steps and are more suitable for training large datasets as compared with traditional methods. Recently, in the medical field, convolutional neural networks (CNN) are more dominated than other techniques [11, 12].

As per the investigation, for automatic brain tumor detection, deep learning is a promising approach, and complex features are learned directly from input data. Deep learning approaches had been popular in the domain of computer vision due to their outstanding performance [13]. But it is required to train the samples without over-fitting and reduce the consuming time to the annotation of 3D ground truth MRI images [14].

In this survey, we have studied recent and popular Deep-Learning techniques to segment and categorize tumors from images of MRI including AI, ML methods, and DL methods.

This put forth, paper is structured accordingly: Section II is providing an overview of brain-tumor segmentation and classification; Section III and IV will provide the overview of various deep learning algorithms.

II. Techniques for Brain-Tumor Segmentation

The process of partitioning the image (2D function) into disjoints objects and used to identify or locate the object boundaries. The ultimate goal of analysis is to detect the ROI ("region of interest") such as location and its extension. In brain tumor segmentation techniques, the abnormal tissues are separated and identified from normal tissues [15].

Medical imaging technology plays a crucial role present in the medical field. So, the segmentation of the brain tumor region with the help of MRI scanning reports is difficult at the primary level due to overlapping of tissues, boundary inefficiencies, dimensional differences i.e., size and shape, abnormalities, position, or location of the tumour. [16]

Structural Segmentation: These image segmentation techniques are depending upon the data of the structure of the desired part of the image that comes under structural segmentation techniques.

Stochastic Segmentation: This type of segmentation technique works on the discrete pixel value of the input image unlike structural segmentation techniques [17].

Hybrid Segmentation Techniques: The combination of both structural and stochastic segmentation techniques is referred to as hybrid segmentation techniques.

Depending on the human interaction, the techniques of segmentation are classified into i) manual, ii) semi-automatic and iii) automatic segmentation techniques.

A. *Manual Segmentation*

In this, identifying the tumor part by the professional expert and they use a specialized tool for tumor assessment. The expert must have proper training, experience, and knowledge in the anatomy of the brain. The manual analysis of MRI reports of human brain for finding the exact boundaries of the tumors by physicians is a complicated, challenging task, and prone to error because of little or no ample brightness the reports obtained pose small amount of contrast MRI images and similarities of intensities among brain cell organelles [18]. The physical assessment of tissues in brain requires more prior knowledge and is time taking tasks to diagnose the patient. Fig. 2 depicted the edema (red-swelling), necrotic (yellow-dead), and active tumor (purple).

B. *Semi-Automatic Segmentation*

This segmentation requires both human operators and computers. To initialize the segmentation process, human interaction must be required and results depend on the human operator. It consumes less time as compared with manual segmentation. Example of semi-automatic techniques is region-growing, tumor-cut method, and active contour models, etc. [18, 19].

Fig. 2. Anatomical Segmentation Manually by the Intersection.

C. *Automatic Segmentation*

In this method, the human operator is not required. To solve the problem of the segmentation task, it combines both prior knowledge and artificial intelligence. There are two types of techniques as discriminating and generative methods [18, 19]. Supervised learning is one of the examples of the discriminating methods. In this, the relationship between the annotation and input image is learned through a large dataset. Unlike supervised learning, the unsupervised learning process uses the data without labels, and they are trained using the loss functions to obtain the patterns considering principal component analysis (PCA) and clustering methods [20]. Due to the complexity of (Because of high complexity (medical datasets), the machine learning techniques are not able to train the data. Recently, deep learning methods have earned a reputation due to their outstanding performance in particularly brain tumor segmentation and learning the parameters directly from data sets. The re-generative methods are utilizing the previous information involving the presence of different tumor forms [21].

III. Overview of Deep Learning Methods

The class of machine learning is deep learning; it can use multi-layers to learn multiple features directly from original data. In this section, the DL- concepts, techniques, and architectures for medical image analysis have been surveyed.

A. Neural Networks

Neural networks (NN) are the basis for deep learning methods and one type of learning algorithm. This NN has learned useful features from raw data and formed by connecting the neutrons by directed links [22]. In the layers, the neurons are organized.

There are three layers (three different layers) such as i) input layer, ii) hidden layer, and iii) output layer. Typical FFNN by composing of three layers shown in Fig. 3.

In input layer each neuron is connected to another neuron in the upstream layer's output. Similarly, each neuron's output is coupled to all the neurons in the downstream layer's input. The weight is adjusted in each link during the learning process [22, 23]. The network's topology immediately forms an acyclic graph, and the network is known as a "FFNN" which refers to Feed Forward Neural Network" in which every neuron is linked or interconnected to the neurons in next layer. The deep neural network is made up of multiple layers, or hidden layers.

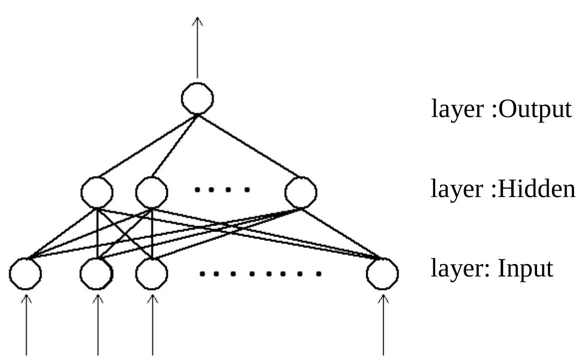

Fig. 3. Typical Structure of FFNN with Three Layers.

Recently, in a supervised manner, all the methods are trained to make easier the training procedure. There are more fashionable architectures utilized in the analysis of health care domain: convolution neural networks (CNNs) and recurrent neural networks (RNNs) [21, 24]. The CNNs are gaining massive popularity to solve problems in medical field as compared to the RNNs. The overview of these methods is given in the following section.

B. Convolutional Neural Networks (CNNs)

The CNNs are used to work on convolutional operations and one type of neural network. There are two types of methods such as traditional and DL methods. The learning approaches in statistics are applied for the classification of low-level brain tumors, which is a regular task in conventional machine learning methods. The CNNs are the dominant area in the last years for segmentation of brain tumors and requires fewer pre-processing techniques and is suitable for training the large datasets than conventional techniques [25].

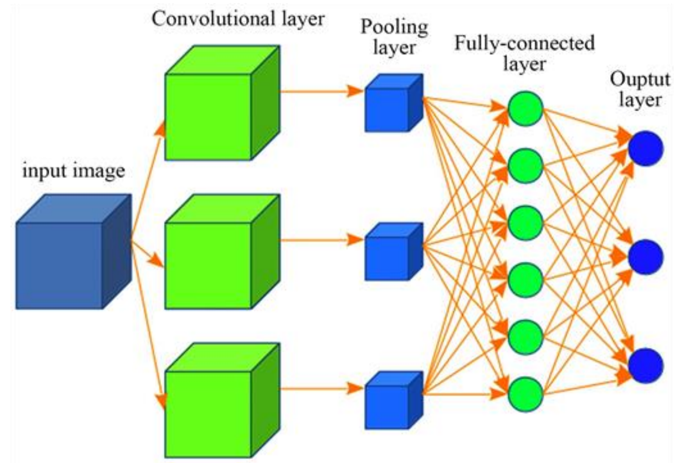

Fig. 4. Typical Structure of CNN.

Nowadays, to solve computer and medical image problems CNN is one among the dominant models, especially for segregation of diverse kinds of brain tumours. The CNN has many layers as shown in Fig. 4 that are transforming the input images into output (normal/abnormal) by using convolutional filters while learning the high-level features [26]. The CNN models have been learning the spatial features in the given data. The first convolutional layer can learn the low edges and second layer will learn high-level features. Next, the units of convolutional layers shrink the number of parameters to learn by distributing the weights. Thereby, increase the efficacy of the network [27]. Node graph for CNN is indicated in Fig.5 (a)

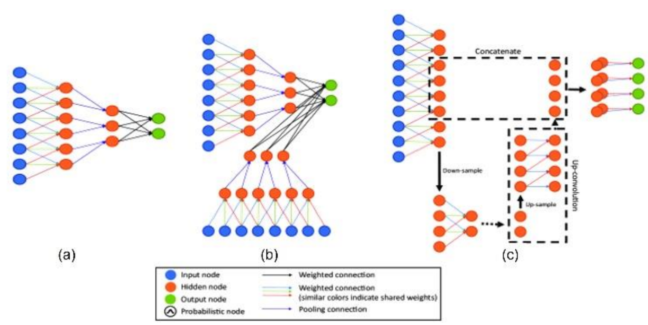

Fig. 5. Node Graph of 1D Representation of CNN Architecture used in Medical Imaging. (a) CNN, (b) Cascaded CNN, and (c) U-net.

The MLTs and CNNs majorly differ where the network shares the weights to perform the convolutional operation, no need for separate detectors to learn, and weights do not depend on the original image size [28]. And also, due to the pooling layer in the CNNs the neighborhood pixel values are accumulated by using the "max or mean" functions [27, 28]. Regular neural networks (completely connected layers) are attached at the conclusion of CNN, but the weights are not shared. The distribution over classes is constructed by applying the SoftMax function and sending the activations into the final layer. Maximum likelihood [29] is used to train the network.

The layers of convolution are learning the local and complex features in the hierarchy from the original given data. To summarize the key features, the Pooling-Layer is included in the middle of consecutive convolutional layers to decrease the enormous parameters and then forwarded to downstream layers. The translation invariant was created to identify the learned patterns, irrespective of geometric transformations [30].

IV. DCNN: Deep Convolution Neural Network

There are different architectures proposed by researchers such as single pathway, dual pathway, cascaded, and U-net. All these architectures are briefed below:

A. Single Pathway

The architecture of a single pathway is looking like a feed-forward deep neural network (FFDNN) and it is a basic network for remaining architectures. In this single path, information is passed down from one of the input layers to the other layer of classification. The 3-D 'single path CNN' was proposed by Urban et al. [31]. This architecture consists of the completely connected convolutional layer as a classification layer and can classify multiple 3-D pixels into one. In [32] every image from the sensory system is supplied to the different 2-D CNN and features from the results of CNN are utilized to train a random forest classifier. The neighbourhood information is obtained from XX, YZ, and XZ planes near each center pixel. In convolutional layers, small kernels have been used by Pereira et al. [33], which can learn more features by obtaining the very deep and deep medic networks. The proposed architectures got a 1stand2ndplace in 'BraTs-2013' and 'BraTs-2015' challenges respectively.

B. Dual Pathway

Pixel-wise classification will be performed in many segmentation approaches, here extract the input patches from input MRI image, and then without considering the neighborhood information central pixels labels were predicted. Infiltrating the process can be risky and makes ambiguous boundaries. So, to achieve better results only local information is not sufficient. To avoid this problem, the authors [34] mix the neighborhood information by employing CNN with dual-path data streams. These dual paths were mixed to impact each pixel label prediction. Among two paths. The visual elements of the region near each center pixel are represented by one of the pathways. The second stream will relate to global information, and it will include the location of the discovered patch in the brain [35].

C. Cascaded Architecture

This architecture will make the multi-scale label prediction independently from others as compared with the dual-path way. The output of the CNN was chained with the other. There are several architectures, among them, input cascade is one of the most important architectures and used to chain the secondary CNN with contextual information. The typical multi-stream CNN is shown in Fig. 5 (b). The local pathway concatenation is a cascaded architecture in which the first CNN's output is sequenced and added with second CNN's first hidden layer output regardless of its input [36].

Another important cascaded architecture is the hierarchical segmentation [37], in which brain tumor segmentation of brain tumor region was accomplished by decreasing the "multi-class segmentation challenge" into a "multi-stage binary segmentation" problem. It uses the hierarchical architecture of tumor sub-regions to reduce false positives while simultaneously resolving the inherent imbalance problem. The entire tumor was segmented from the reports of MRI which has been given as inputs at the initial stage of the design, and then a boundary box was used in the second step. Next, separate the remaining sub-regions using either multi-class intra-tumor segmentation or successive binary segmentation. [38].

D. U-net

The U-net architecture [39] is constructed exclusively for biomedical image segmentation and looks like an encoder and decoder network. A U-shaped design consisting of an encoder at the contracting path and decoder at the expanding side which entirely builds up the U-net. In the contracting pathway, the ReLU layer and the max-pooling layer come after the two convolutional layers. The spatial data decreases as the path contracts, while the feature information increases. From contracting to skip connecting, the expanding path comprises a sequence of up-sampling processes paired with high-resolution features. The typical U-net showed in Fig. 5 (c).

V. CNN Models for BraTS

The current methods for segmenting and classifying kinds of tumours that affect human brain from MRI data is discussed in this section. The manual assessment tissue organelles of brain require an ample prior knowledge, are time taking tasks, and prone to error during the diagnosis process. Therefore, these issues motivated to development of automated tumor detection techniques by several researchers, and it becomes a significant area for research in medical image processing. This review article mostly concentrates on the segmentation and classification processes based on traditional AI, MLT, and DLM in the last five years.

The literature has highlighted several automated approaches in the domain of health care image analysis to diagnose the health issues such as tumours, lung cancer [19], skin cancer [20, 21], and more [22, 23]. Many strategies for pre-recognition and categorization of brain tumors are offered as a result of all of them.

Kumar Agrawal, Ullas, and Pankaj Kumar Mishra [40] studied various state-of-the-art algorithms for detecting and classifying tumors accurately. They revealed that deep learning may be used in conjunction with several transfer learning approaches to construct a systematic and efficient approach for the early identification of tumours in brain in this proposed study.

Rehman, Amjad, and colleagues [41] suggested a novel DL-based technique for classifying microscopic brain tumours. The authors designed the 3D architecture of CNN, draw out the brain tumour and then send it to the pre-trained CNN model for parameter extraction. Next, to choose best features a correlation-based selection approach is employed. The chosen parameters are validated by employing the FFNN for the last classification. The authors utilized BraTS 2015, 2017, and 2018 for validation and achieved more than 92.67% of accuracy.

Sharif, Muhammad Imran, et al. [42] presented a new automated DL- method to classify the multi-class brain tumors. In the proposed method, the densenet201 pre-trained DL model was trained by deep transfer of imbalanced data learning. The average pool layer is used to retrieve the training model features. Two methods are used to pick the features. i) entropy-kurtosis-based high feature values (EKbHFV) and ii) metaheuristic-based modified genetic algorithm (MGA). The non-redundant serial-based approach is used to fuse the EKbHFV and MGA-based features. Finally, a multiclass SVM cubic classifier is used. They concluded that the presented method has achieved an accuracy of about 95.5%.

Khan, Amjad Rehman, et al. [43] presented new DL techniques to classify the tumours from MRI brain images. The author’s method consists of pre-processing, segmentation using the K-means technique, and classification using the fine-tuned nineteen-layered visual geometric group (VGG19) model. To enhance the scale of the available data, the synthetic data augmentation idea is presented. The Put forth method outperformed earlier when compared with accuracy, the put forth model outperformed the previous state-of-the-art approach.

Khairandish, Mohammad Omid, and colleagues [44] created a hybrid model that uses CNN and SVM for classification and threshold-based segmentation for detection. To categorize benign and malignant tumors, the authors used a publicly available dataset. The suggested hybrid CNN-SVM technique achieves an overall accuracy of 98.4959 percent.

TAS, Muhammed Oguz, and Semih ERGİN [45] in this survey, the authors studied the segmentation of tumors from abnormal brain MRI images with DL and K-means approach. The proposed method was extracting the tumor area automatically with an accuracy and sensitivity of 84.45% and 95.04% respectively.

The authors [46] have been proposed the Google Net approach depending upon the CNN DL approach to classify the different types of tumors from MRI brain images and to overcome the difficulties in the classification of attributes such as variants in texture, size, and shape. The authors use MRI datasets to perform five-fold cross-validation and authenticated the put forth system's performance in terms of "area under the curve" (AUC), F-score, recall, precision, and specificity. The proposed system with transfer learning provides the classification accuracy of 97.8% and 98% with the multiclass SVM method.

In [47], the stationary wavelet transform (SWT) approach and modern growing convolution neural network (GCNN) (alarming CNN) was developed by the authors in this study to improve the efficiency of an automated brain tumor segmentation system. SVM and CNN have done better than the suggested work in all aspects.

For automatic segmentation, the authors [48] offered enhanced convolutional neural networks (ECNN) with loss function optimization via the BAT algorithm. They presented the optimization-based MRIs image segmentation. To overcome the overfitting problem, assigned the lesser weights to the network. The efficacy of the proposed system was authenticated by utilizing the different popular brain tumor datasets. The overall results indicate that the presented method shows better performance.

The segmentation in a DL approach [49] is done with CNN. The Convolution Neural Network has deep architecture; this approach employs three tiny kernels. For the pre-processing of pictures, intensity normalization and data augmentation were used. The method is evaluated using the famous dataset (BraTS 2013 and BraTS 2015).

The authors [50] presented a solution for the low accuracy of brain tumor segmentation using DL techniques. They studied MRI images in different angles and applied different networks for segmentation. Evaluated the effect of separate networks and compare them with a single network. The dice score 0.73 and 0.79 is achieved with single and multiple networks, respectively.

The DCNN-F-SVM was presented by Wu Wentao, et al. [51] for segregation of various types of brain tumour. The proposed segmentation model has three stages: first, DCNN is trained, then predicted labels are produced from the trained DCNN, and finally, the DCNN and an integrated SVM is a deep classifier which is connected in series. They used the BraTS and self-made datasets to run each model for brain tumors segmentation. The authors conclude the presented methodology has performed for brain tumor detection better than DCNN and SVM classifier.

Sun, Li, et al. [52] presented segmentation of brain tumor and glioma survival anticipation utilizing the based framework. For tumor segmentation, the researchers used multimodal MRI scans and three 3D CNN designs. For survival prediction, 4,524 radiomic characteristics are retrieved from segmented regions, and potent features are opted making use of both decision tree and cross-validation techniques. They trained a random forest model to predict the patient’s survival rate. The authors were preferred BraTS 2018 and achieved 61.0% of classification accuracy for short, mid, and long survivors among 60+ participated teams.

Bhandari, Abhishta, Jarrad Koppen, and Marc Agzarian [53] investigated the potential use of CNNs by studying radiomics and analyzed quantifiable features tumours including texture, shape and ability to forecast clinical consequences such as survival and diagnosis. The authors also investigated the role of CNNs intended for brain tumors segmentation through the education viewpoint and performed the literature review.

Sharif, Muhammad Irfan, et al. [54] presented a non-passive learning feature selection strategy for detecting and distinguishing brain cancers. The contrast enhancement is first fed into SbDL for the development of the saliency map, and then it is transformed to binary using thresholding algorithms. Deep feature extraction was done using the inception V3 pre-trained CNN model was utilized for extraction of deep features for the purpose of classification. Next, for better texture analysis, the features are sequenced and aligned with dominated rotated (DRLBP) and particle swarm optimization (PSO) is used to optimize the concatenated vector. The SbDL segmentation and classification strategy are applied on BARTS 2017 and BRATS 2018 to validate. The presented method outperforms for classifying and segregation of brain tumours) with accuracy of 93.7% and 92% respectively.

Khan, Muhammad A., et al. [55] developed an automated system based on marker-based watershed segmentation for extraction and classification of brain tumors using MRI images. The first contrast of the tumor was enhanced by using the gamma contrast stretching technique and then the segmentation process was performed using the marker-based watershed algorithm to detect the tumor exactly. Next, by using the chi-square max conditional priority feature method, the features are selected and then fused by the serial-based concatenation method before classification. The SVM was applied to classify the tumors using the datasets such as Harvard, BRATS-2013, privately collected. The overall results revealed that the presented system performs than existing systems with high accuracy.

VI. DATASETS

On selected datasets of tumor MRI scans, all of the strategies described in this work were tried. The research groups interested in automatic tumor segmentation from abnormal brain images over the last five years. The researchers have used the different private and public datasets to evaluate the various algorithms. A number of datasets are accessible for training and testing purposes. The challenges of benchmark datasets provide the publicly available datasets such as DICOM [56], BRATS [57], BRATS 2013, 2013, 2015, 2016, 2017, 2018, and 2020), MICCAI [58], Brain Web [59], Harvard business school [60], Internet Brain Segmentation Repository (IBSR)[61],nyrosynth.org [62], ABIDE [63], National Bioscience Database Center (NBDC) [64], Med Pix, PGIMER dataset [65], SPL database [66] etc.

VII. PERFORMANCE EVALUATION METRICS

The effectiveness of segmentation or classification methods can be measured in a number of ways. To demonstrate their results, the authors employ various performance measure parameters. The analysis of traditional methods is commonly evaluated by mean square error (MSE), peak signal to noise ratio (PSNR), entropy, and correlation. Among various image quality assessment parameters for analysis of the result, some of the overlapped based parameters are briefed below:

Accuracy: The ability to determine the precision or proximity of the tumor is referred to as accuracy. The following factors influence it:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

True positive is denoted by TP, whereas true negative is denoted by TN. False-positive and false-negative are represented by the letters FP and FN, respectively [56].

Precision: It denotes the consistency of two or more values. The precision formula is as follows:

$$precision = \frac{TP}{TP + FP} \tag{2}$$

Where TP represents the true positive and FP represents the false positive. The fraction of true positives is referred to as precision. The valid positive results are evaluated by dividing valid positive outcomes aided by the segmentation algorithm. Similarly, the pixels are break down into the cluster and pixels that are of that cluster

Sensitivity or recall or true positive rate: It's the ability to find a tumor or any other affected location [50]. The mathematical equation is written as follows:

$$sensitivity = \frac{TP}{TP + FN} \tag{3}$$

The TP denotes true positive and FN denotes false negative. Sensitivity is the proportion of correctly segmented images to all segmented images. The greatest results for accuracy, precision, and sensitivity suggest that the brain tumor can be recognized precisely and without ambiguity.

Confusion Matrix: It is used to give required information about the actual and predicted results by a particular method. The confusion matrix revealed in Table I that was seen below:

TABLE I. THE REPRESENTATION OF THE CONFUSION MATRIX

Type	Predicted class 1	Predicted class 2
Actual class 1	T_P	F_N
Actual class 2	F_P	T_N

SDE-Segmentation Distance Error: It is used to assess the effectiveness of segmentation procedures and the equation is denoted as

$$SDE = \frac{\|\varphi F - \varphi D\|^2}{\|\varphi D\|^2} \tag{4}$$

Where φF is the terminal contour and φD is the aspired contour derived from the brain tumor ground truth image. The SDE returns the normalized contour between the intended and terminal contours. The SDE range from 0 to 1, here 1 indicates the inadequate segmentation [32].

Jaccard Similarity Index (JSI): The JSI is defined as the ratio of common voxels in the input image (X) to the union function, or the collection of voxels in the input image (X) and segmented output image (Y) [8, 17]. The JSI mathematical equation is given by:

$$JSI = J(X,Y) = \frac{|X \cap Y|}{|X \cup Y|} \quad (5)$$

It is a scale that runs from 0% to 100% in terms of similarity between the input image and the segmented image. The greater the similarity, the higher the percentage.

SSIM -Structural Similarity Index Measure: The SSIM is a perceptual parameter, which means that image quality may suffer as a result of data compression, lack of data transport, or other image processing procedures. This expression is provided by:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (6)$$

Where μ_x and μ_y are the mean, σ_x and σ_y are the variance, and σ_{xy} is the covariance of x and y. The values c_1 and c_2 are constants. A larger SSIM value guarantees improved brightness, contrast, and structural material quality [55]. In addition to these characteristics, computation time and iteration count are utilized to calculate the performance of the suggested approaches.

VIII. Hardware and Software Tools

Nowadays various open-source softwares are used by researchers to speed-up the deep learning systems. This section has covered a brief description of hardware and software used in research papers.

For deep learning purposes, there is the availability of computing libraries such as GPU and CPU. The GPUs have been performed parallel computation with a high execution rate as compared with the CPUs. The GPUs hardware in deep learning is 10-30 times faster than CPUs. These libraries of GPUs also provide various operations implementation in NN i.e., convolutions and user friendly. Due to the popularity of DL, there is more availability of open-source software packages.

Caffe [67] is first established for computer vision applications by graduate students (Jia et al., 2014) at Berkeley and supports C++ and Python interfaces. This deep learning framework is not only used in computer vision applications, but it can also use in other fields such as robotics, neuroscience, and astronomy. For deep learning, from training to architecture development, provides the complete tool kit with good examples. It allows the user to implement the building models and models of deep learning with various algorithms.

TensorFlow [68], developed by Google (Abadi et al., 2016) for large-scale machine learning applications and supports the C++ and interfaces of Python. It is end-to-end distributed deep learning and supports the data flow graphs execution in mobile devices or heterogeneous devices. It is designed for fast experimentation with a deep learning model using a complete toolbox and simply the parallelism of the model.

Theano [69] was built in the Montreal lab called MILA (Bastien et al., 2012) and offers Python interfaces. It is used to execute and compile the mathematical expressions by syntax NumPy quickly using both GPUs and CPUs, especially for large-scale dataflow. The other high-level software packages constructed upon the Theano consider Pylearn2, Keras, and Lasagne.

Pytorch [70] is an important approach to construct the computational graph dynamically rather than static computational graph before running the model and open-source framework of deep learning. It is flexible, powerful, and easy of debugging (Collobert et al., 2011). The Pytorch is suitable for the production and execution of models on edge devices. It is used in Facebook AI research.

Pylearn2 [71] allows the user to construct or implement the machine learning models in an arbitrarily and free (open source) machine learning library. This library is flexible and easy to use. But unfortunately, due to the lack of active developers, it is fallen as compared with other frameworks.

Keras [72] is one of the rapidly developing application programming interfaces (API) for various applications of deep learning and supports multiple data-flow graphs like Theano. To run the experiments with models Keras consist of simple APIs which has provision to run in mobile devices and also in browsers. This platform was adopted for research areas and industrial applications due to its simplicity of usage (user-centric approach).

Lasagne [73] In Theano, the Lasagne is a trivial library for building and training NNs. To run the Lasagne, you will need Python 2.7 or 3.7, and instructions are running in MAC or Linux systems. It has the capability of powerful mathematical computations and constructed upon the Theano.

IX. Summary and Discussion

Deep Learning (DL) based approaches for segregation brain tumour have recently sparked a lot of interest. In brain tumour segmentation, deep learning systems are trained on big datasets to segment the tumour from MRI images by learning a hierarchy of complicated properties straight from data. As a result, CNN-based models are the most used in medical image analysis, with success in fields including natural language processing, audio identification, and brain tumour segmentation. For instance, in Fig. 6, CNN was used to segment brain tumors using a single node into CNN. Input, convolution with nonlinearity correction using ReLU, overfitting correction using pooling, feature map flattening into a column, and finally insertion into the neural network.

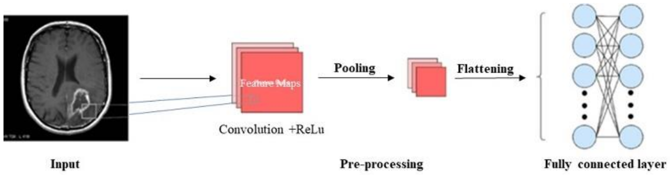

Fig. 6. Input the Image into a Single Node within a CNN.

In this work, recently published papers have been reviewed. It is clear that DL methods play a crucial role to address the problems faced in automated brain tumor segmentation. Pre-trained CNNs are employed as feature extractors in recent studies, and these networks are installed and employed directly on the medical images for a specific purpose. In the previous two years, end-to-end trained CNNs have been favored for medical image analysis interpretation. Nowadays, deep learning approaches are integrated with traditional machine learning handcrafted methods. In recent works uses the U-net and ensemble methods to resolve the problem of segmentation of a brain tumor [74-78].

TABLE II. THE COMPARISON OF VARIOUS DEEP LEARNING TECHNIQUES BASED ON DATASETS AND ACCURACY

Author, Year	Method	Dataset	Accuracy (%)
K. Agrawal, 2021[40]	Transfer Learning method	BraTs 2018	97.17
Rehman, 2021[41]	3D-CNN Architecture	BraTs 2018	95.53
Sharif, 2021 [42]	Entropy–Kurtosis-based High Feature Values (EKbHFV) and modified genetic algorithm (MGA)	BraTs 2019	95.0
Khan, 2021 [43]	Deep learning approach- finetuned VGG19	BraTS 2015	94.06
Khairandish, 2021 [44]	hybrid CNN-SVM	BraTs 2019	98.49
TAS, 2020 [45]	Traditional Deep Learning Technique		84.45
Wu, 2020 [51]	DCNN-F-SVM	BraTs 2018	96.0
Sharif, 2020 [54]	Pixel Increase along with Limit (PIaL)	BraTs 2018	93.7
S. Deepak, 2019 [46]	deep CNN features via transfer learning	BraTS 2017	98
Mamta Mittal, 2019 [47]	Growing Deep Convolutional Network (GCNN)	BraTs 2018	97.7
Thaha, 2019 [48]	Enhanced Convolutional Neural Networks (ECNN)	BraTs 2015	92.0
Sun Li, 2019 [52]	3D CNN architectures (Cascaded Anisotropic CNN, German Cancer Research Center NET - DFKZ Net, 3D-U-Net)	BraTs 2018	91.0
Sobhaninia, 2018 [50]	LinkNet network	BraTs 2015	89.12

The ensemble approaches improve the robustness of every approach by combining the results of segmentation and providing better performance as compared to several models. The single U-net-based models support the argument. The overview of recent approaches used for brain tumor segmentation along with its accuracy is shown in Table II. For deep learning algorithms, we need an enormous quantity of training data to simplify properly invisible data and poses many challenges in the domain of medicine. It requires an experienced neuro-radiologist before applying to the supervised training.

So, it's an expansive, large memory resources, and time-consuming task. But recently the BraTS challenges provides training and testing to users and due to proper training, the over-fitting problem will be reduced. At the same time, the researchers have implemented data augmentation to avoid the problem of unavailability of large-scale datasets. The computational and memory requirements increased further due to 3D deep learning models.

As per the literature, the authors have used costly mathematical functions, well software libraries, multi-GPU environments and train the data in a distributed manner. To enhance the correctness durability of segmentation algorithms, authors must carefully initialize the hyper-parameters, employ proper pre-processed approaches and use Latest training methods

X. CONCLUSION

We discussed methods for segmenting brain tumors, different architectures of deep learning methods for automatic brain tumor segmentation, a literature review of recently published papers, tools for implementing the algorithms, dataset availability, and appropriate performance metrics to estimate the performance of each method in this paper. As compared with traditional techniques, the deep learning methods are still superior due their robustness and performance. The novel architectures of Deep-Learning have a great potential to avoid the inherent class imbalance problems in tumor segmentation by using proper pre-processing, initialization of weights, and sophisticated training methods. In many segmentation techniques, due to the lack of a large-scale training dataset, its performance will be degraded.

This paper contains an overview of contemporary strategies for segmenting and classifying brain tumors using MRI data. The goal of the presented survey is to demonstrate briefly about the most commonly used strategies for segmenting and classifying tumours. Various tumor segmentation techniques (manual, semi-automatic and automatic), deep learning methods (NN, CNNs, and DCNN), and different architectures are used in DCCN.

This paper consists of a review of the recently published research articles from science direct, IEEE explore, etc. The literature covered the ML techniques, DL methods, and hybrid methods for abnormality segmentation from MRI brain images. This paper also contains publicly available datasets or benchmarking challenges such as BraTS 2012-202, MICCAI, Harvard University, and Brain Web. As per the literature of various published papers, the authors have been primarily used datasets are BraTs-2013 followed by BraTs-2015.

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