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SURVEY

Deep Learning Techniques for the Classification of Brain Tumor: A Comprehensive Survey

AYESHA YOUNIS [1], QIANG LI [1], MUDASSAR KHALID [2], BEATRICE CLEMENCE [3], AND MOHAMMED JAJERE ADAMU [1,4], (Member, IEEE)
[1]School of Microelectronics, Tianjin University, Tianjin 300072, China
[2]School of Engineering, Chulalongkorn University, Bangkok 10330, Thailand
[3]Department of Computer Science, Tianjin University of Technology and Education, Tianjin 300222, China
[4]Department of Computer Science, Yobe State University, Damaturu 600213, Nigeria

Corresponding author: Qiang Li (liqiang@tju.edu.cn)

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ABSTRACT Researchers have given immense consideration to unsupervised approaches because of their tendency for automatic feature generation and excellent performance with a reduced error margin. Deep learning (DL) models are emerging as vital methods for image analysis in medical fields, such as classification, segmentation, and reconstruction. Deep learning relies on learning hierarchical features and data representation, making it superior to its antecedent. Deep learning models efficiently discover descriptive information about the optimal representation of various brain tumors when applied for brain tumor classification from MRI. Despite various efforts, there remains a gap in the current literature for inclusive representation of recently developed deep learning-based classification methods. The current study attempts to fill this gap by briefly reviewing the current state of the art on brain tumor segmentation and classification methods while focusing on deep learning methods. The proposed survey dedicates itself to review the current state of the art on automated classification techniques for brain tumor MRI to produce an inclusive picture of the most recent and worthy of adoption models proposed in this area. Despite various attempts to conduct surveys on brain tumor segmentation and classification techniques, no such study could be found in the current literature that has dedicated its focus to the most effective approach toward classification. This research begins by identifying major brain tumor segmentation and classification classes while presenting its focused area and reviewing the most recent state-of-the-art classification approach, the deep learning-based classification method. The powerful learning ability of deep learning mechanisms has been reviewed for their performance, and a comparison between them is presented to encourage its applications. Future recommendations and directions are also drawn up to establish a pursuable course for welcoming widespread adoption of potential applications in the area.

INDEX TERMS Deep learning, machine learning, classification, segmentation, brain tumor, MRI.

I. INTRODUCTION

Brain tumor (BT) refers to an unwanted and uncontrollable development or growth of cells in the brain. A life-threatening situation could be generated due to such development because it tends to affect other body parts. Also, the human brain has physical limitations to endure this unwanted development of cells. In the treatment and diagnosis of this disease, a pivotal role is played by advancements in imaging technology. Various imaging methods are available today for brain tumors that may vary from MRI to CT scans. A great deal of information is contained in a Brain magnetic resonance

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(MR) image regarding the multi-dimensional structure of the human brain. Brain tumors are known to be the most complex and dangerous among all forms of tumors. Various methods have been developed to identify tumors from MR images of the brain [1].

For the application of machine learning, the brain tumor has stirred a particular area of interest for researchers due to the complexity and information processing requirements posed by the diagnosis process. In modern neuroimaging, magnetic resonance imaging for tumor diagnosis has proven to be a major pillar as it can assist with the characterization of the tumor's functional, metabolic, cellular, and structural properties [2], [3]. Cerebrospinal fluid (CSF), gray matter (GM), and white matter (WM) contained in a healthy brain are subjected to scanning in conventional MRI [4]. Their water content determines major variations in these tissues during a structural MRI scan. The cerebrospinal fluid is nearly 100% water, whereas the white matter is 70% and the gray matter is 80% water [5]. Classification can be done based on these normal tissues nd tumorous brain parts such as edema, necrosis, and core tumors [6].

A variety of criteria can be employed for the classification of brain tumors. A highly appropriate approach for radiological use was proposed by WHO that carries out an in which layer-based classification of the tumor. Four-layer hierarchy could be found in this scheme [7]. Still, based on their origin, brain tumors can easily be grouped into primary and secondary tumors [8]. The tumors originating from the brain are regarded as primary tumors and are assigned their names from their source cell type. They can be malignant (cancerous) nd benign (non-cancerous) regardless of their prime origin. Slowly growing Benign tumors cause lesser invasion and spread, yet the brain may experience pressure and compromised functioning.

Meanwhile, a secondary brain tumor originates from other parts of the body. For instance, a secondary brain tumor can be caused by bladder cancer, kidney cancer, melanoma, breast cancer, lung cancer, certain germ, and testicular cell tumors [8], [9], [10]. Unique biological, radiographic, and clinical characteristics are found to be associated with each of these tumors.

MRI images are processed to support radiology decisions by applying classification and segmentation in different automated learning approaches. Unsupervised and supervised approaches have been tested in this regard. In the supervised approach, a certain level of expertise is required to classify brain tumors for extracting optimal features and selection techniques. Meanwhile, the computational complexity of automated models plays its role in substituting required manual expertise [11].

In the recent past, researchers have given immense attention to unsupervised approaches [12] mainly because of their tendency for automatic feature generation and excellent performance with a reduced margin for errors. Models with deep learning (DL) are emerging as vital methods for image analysis in medical fields, such as for even classification [13], segmentation [14], and reconstruction [15]. So, brain tumor classification and segmentation technique has been an area of attention for scholars, and various attempts have been made to improve the existing practice and theory. Despite various efforts, there remains a gap in the current literature for inclusive representation of recently developed deep learning-based classification methods. The current study attempts to fill this gap by briefly reviewing the current state of the art on brain tumor segmentation and classification methods while focusing on deep learning methods. The variation among reviewed techniques can be accounted for through an understanding of differences in performance parameters revealed by the previous scholars [16].

A. RESEARCH NOVELTY

The existing state-of-the-art lacks a dedicated and up-to-date account of effective classification techniques and approaches toward brain tumor MRI. The novelty of this research lies in its unique pursuit towards narrowing the focus of exploration towards a consensual approach to brain tumor classification that can further be encouraged for its adoption across the medical field.

B. RESEARCH CONTRIBUTIONS

Despite various attempts to conduct surveys on brain tumor segmentation and classification techniques, no such study could be found in the current literature that has dedicated its focus to the most effective approach towards classification. This research begins by identifying major classes of brain tumor segmentation and classification while presenting its focused area and reviewing the most recent state of the art on the most effective classification approach, the deep learning-based classification method.

C. PAPER ORGANIZATION

After introducing the topic to readers, the paper includes a literature review and a section on various segmentation methods for a brain tumor MRI. The fourth section is dedicated to brain tumor classification methods for MRI and their types, after which deep learning-based brain tumor classification is covered explicitly in the fifth section. The paper's methodology follows a comprehensive review of deep learning-based brain tumor classification. The discussion comes next in the paper, and the conclusion is the paper's final part, where future directions are also provided for researchers.

II. LITERATURE REVIEW

The pursuit of sovereign brain tumor classification and segmentation technique has been an area of attention for scholars in the field to facilitate practitioners successfully diagnosing the disease. Many attempts have been made to survey the current state of the art in this field to outline the potential techniques of brain tumor segmentation and classification [17]. However, gaps and limitations are still residing in the current state of the art regarding explicit evaluation of deep learning models' performance, as their domination is well established against a list of other approaches taken so far. Furthermore, surveys conducted so far had limitations and gaps [1].

Authors in [18] conducted a literature review survey for various segmentation techniques for brain tumor classification. They included supervised and unsupervised machine learning mechanisms and a review of deep learning and Thresholding. The limitations of the survey exist in terms of its inadequate focus on brain tumor classification methods as they only reviewed the pros and cons of available algorithms. There was restricted discussion on segmentation techniques, and the performance of techniques was not considered. Furthermore, the study was limited to evidence from studies published before 2018, posing a major limitation on its contribution in the current context.

An in-depth hierarchical classification of brain tumors was presented in the review by [19]. The survey covered a wide range of literature, from conventional machine learning to deep learning techniques for classification of brain tumors. However, the limitations are there while considering its contribution to the current state of the art, as it only reviewed literature published till 2019. In contrast, a wide-ranging number of contributions have been made since after that. Also, another limitation of a survey by [19] could be highlighted in terms of its limited coverage of classification and segmentation literature.

Another survey was conducted by [20] 2021 on brain tumor segmentation techniques based on deep learning mechanisms. An in-depth presentation of the techniques was carried out. However, there still remain several limitations in their review. A major limitation lies in the limited consideration of the performance of segmentation techniques, as it was only viewed for the BRATs dataset.

A Survey by [21] highlighted various brain tumors segmentation approaches such as unsupervised and conventional supervised machine learning, deep learning, atlas, region growing, and Thresholding. Like the rest of the contributions, a few limitations exist for this review because apart from two studies, their survey conducted a chrono-logical examination of research published before 2020, which may prove inadequate and outdated considering the recent developments [22], [23].

Another survey on unsupervised, conventional supervised-based segmentation techniques and Thresholding was conducted in 2021 [29]. Discussion on deep learning techniques in the survey by Sharma and Shukla [29] was very limited, and it lacked consideration of the performance of reviewed techniques posing a major limitation.

Similarly, the survey of [17] provided an inclusive review of the segmentation and classification algorithms for brain tumor classification. They covered conventional machine learning, region growing, and deep learning techniques. Superior performance is established for the deep learning-based techniques for classifying and segmenting brain tumors from MR images. However, there remains a gap in the literature for providing an inclusive review of the deep learning-based brain tumor segmentation and classification methods. The current study attempts to fill this gap by initiating a brief review of the current state of the art on brain tumor segmentation and classification methods while narrowing the focus on deep learning methods in particular. The variation among reviewed techniques can be accounted for through an understanding of differences in performance parameters revealed by the previous scholars.

III. BRAIN TUMOR SEGMENTATION METHODS

A significant number of images are produced when techniques like CT and MRI are applied for brain tumor imaging. A three-dimensional anatomical illustration contains many slices from the individual's brain when subjected to brain MR imaging. Hence, it remains a great challenge and time-consuming for practitioners to manually segment brain tumors from images in MRI. Furthermore, in the imaging process, newly introduced artifacts have produced low-quality images that are very hard to interpret. Consequently, manually generated brain segments are prone to intra and inter-observable variations. To address the problems and assist radiologists, various automatic segmentation approaches have arisen for brain tumor segments, and a wide array of literature contributes to this area. In this stream of research, scholars have projected automated systems for segmentation techniques in brain tumor diagnosis that offers reproducible and objective segmentation, usually closer to the manual outcomes. Such automated techniques can assist in alleviating the challenges emerging in the manual analysis of brain tumors. It can result in an improved pace of brain image analysis, better diagnosis results, and easier treatment follow-up procedures through the tumor progress assessment [23].

Previously, surveys had been conducted on brain tumor segmentation techniques in general. They included machine learning, deep learning, and region growing-based techniques for identification of performance reported, preprocessing techniques, segmentation algorithm, and feature extraction across literature in this area [17]. However, no dedicated effort is reported to this yet for exploring deep learning mechanisms applied so in an inclusive manner. Hence, this research intends to briefly fill the gap by revisiting brain tumor segmentation techniques and narrow downbriefly fill the gap by revisiting brain tumor segmentation techniques and narrow the research to a dedicated review of deep learning techniques' applications. To move toward deep learning classification and segmentation, it is worthwhile to revisit the categorization of classification and segmentation of brain tumors.

A. UNSUPERVISED MACHINE LEARNING APPROACHES

Region-based segmentation is one of the most common techniques of brain segmentation with automated image processing. An image region contains a collection of inter-connected pixels that meet certain criteria of homogeneity, such as texture, shape, or in-tensity values of pixels [24]. Dissimilar region partitioning of the image is used by region-based segmentation for easily isolating the desired region of interest [25]. This type of segmentation technique considers pixel values; for instance, it would consider the pixel's spatial proximity and the variations in gray level differences based on region compactness or Euclidean distance in grouped pixels. Clustering algorithms and region growing is among the most comply employed techniques of region-based segmentation for brain tumors.

A clustering algorithm that partitions images into numerous disjoint groups is a powerful region-based segmentation approach. In this form of region-based segmentation, a given region is assigned as the category for highly similar pixels, while different regions are assigned to pixels showing dissimilarity [26]. Clustering techniques regarded under unsupervised learning have been extensively studied in image segmentation for medical applications. A variety of hybrid techniques [27], [28], [29], subtractive clustering (SC) [27], [28], [29], fuzzy c-means [30], [31], [32], [33], k-means, and many versions of k-means are widely studied clustering methods in the literature. K- means the method is an unsupervised ML algorithm generally applied for segmenting the desired region in the remains of an image. Extensive utilization of k-means could be seen in the testing of brain tumor segmentation, which has offered satisfactory accuracy [29]. Despite various advantages [34], [35], inadequate explanation of the tumor region is associated with the k-means method [34]. Furthermore, other challenges, such as outliers' sensitivity [37] and lack of optimum results in initial centroid selection [35], [36], make it a weaker contender for the segmentation of brain tumors. Many solutions have been proposed to overcome these challenges, such as histogram-based k-means, modified adaptive k-means (MAKM), adaptive k-means [36], and even the spread of the initial cluster centers (k-means++). In Fuzzy c-means (FCM), membership values are assigned to pixels representing the center of clusters containing those meeting the same criteria [39]. It is regarded as a soft-clustering technique and has presented a higher performance in noise-free results against k-means. However, as brain imaging is susceptible to unknown noises, severe performance degradation in FCM is anticipated [41], [42], [43].

Regions with spatially distinguished positions and properties can be used to properly segment region growing based segmentation. Regardless of its potential, it also inherits similarity criterion [38] and noise sensitivity in brain tumor segmentation. Also, identifying a good seed remains a hectic task in growing-based segmentation [38].

B. SUPERVISED MACHINE LEARNING APPROACH

A supervised machine learning approach creates a renovated tumorous pixel classification problem. Various features being extracted are taken as input in the supervised learning models, while pursued segmentation classes are the output vector of the models. Compared to conventional segmentation methods, pixel classification is preferable for the scattered tumor regions in the image of brain tumor segmentation [44]. Hence, in brain tumor segmentation, segmentation techniques have adopted traditional supervised machine learning algorithms [45], [46], [47], [48], [49].

C. DEEP LEARNING APPROACH

In the deep learning method, automatic features are generated to avoid or minimize the handcrafted features. Brain tumor segmentation using a deep learning approach generally involves a schema for passing images through the channel of deep learning building blocks and performing image segmentation based on the deep features. The current literature has introduced many deep learning techniques for brain tumor segmentation. These studies include deep neural networks (DNNs), generative adversarial networks (GANs), deep autoencoders (AEs), long short-term memory (LSTM), recurrent neural networks (RNNs), convolutional neural network (CNN), and deep convolutional neural networks (DCNNs). A convolutional neural network (CNN) is an artificial neural network intended explicitly for undertaking pixel data for image processing along with its recognition. They are considered robust systems with image processing capabilities. Both descriptive and generative functions are performed by CNN using deep learning mechanisms that usually include machines visioning such as video or image recognition. Furthermore, they may also involve Natural Language Processing (NLP) and recommendation systems.

IV. BRAIN TUMOR CLASSIFICATION METHODS

While a huge number of studies were focused on brain segmentation, there has been an equal amount of contribution to the classification of brain tumors through MRI [17]. According to the central nervous system (CNS) tumors classification of the World Health Organization (WHO), a total of more than a hundred and fifty types of tumors can be investigated that are generally characterized as primary and secondary tumors [50]. The tumors originating from the brain are regarded as primary tumors and are assigned their names from their source cell type. In the meantime, a secondary brain tumor originates from other parts of the body. Unique biological, radiographic, and clinical characteristics are found to be associated with each of these tumors. A biopsy is a commonly accepted standard process for classifying brain tumors, though it generally needs definitive brain surgery to take samples [51].

Meanwhile, a non-invasive approach is offered through MRI tumor classification as the sample is not required making it a comparatively safer procedure. Furthermore, brain tumor classification based on machine learning techniques has immense potential to improve diagnosis and anticipate treatment plans. Because of this approach, machine learning-based automatic brain tumor classification from magnetic resonance images remains a relevant area of research where promising results are improvements are sought by academia [52], [53], [54], [55], [56].

A. MACHINE LEARNING BASED CLASSIFICATION

Machines are tasked with achieving improved performance through learning in the machine learning paradigm. Techniques in this field are generally categorized into three types: reinforcement learning, unsupervised and supervised [57].

A certain level of expertise is required in the supervised approach for classifying brain tumors and extracting optimal features and selection techniques. Hidden patterns from unlabeled data are discovered through algorithms of unsupervised learning. Reward signals are used in reinforcement learning, where the sequence of decisions is based on these signals. Promising classification has been reported across academia for the potential of machine learning in brain tumor classification against MR images [58], [59], [60], [61]. Recently, researchers have given immense attention to unsupervised approaches mainly because of their tendency for automatic feature generation and excellent performance with a reduced margin for errors [82], [83], [84], [85]. Deep learning (DL) models are emerging as vital methods for image analysis in medical fields, such as for even classification, segmentation, and reconstruction.

Despite the promising progress in brain tumor classification from MRI images using traditional machine learning algorithms, there remain barriers to achieving the desired results. The barriers are mainly posed by the inadequate descriptive information extraction and ROI detection in the feature extraction techniques based on convention-ally hand-crafted features [62]. Such incompetence resides due to the high-density nature and complex anatomy of brain structure. In contrast to conventional machine learning techniques, deep learning relies on learning hierarchical features and data representation making it superior to its antecedent. Deep learning models efficiently discover descriptive information about the optimal representation of various brain tumors when they are applied for brain tumor classification from MRI. So, brain tumor classification is renovated from an outdated handmade features-driven form to a data-driven problem [56].

B. DEEP LEARNING BASED CLASSIFICATION

A review of the current state of the art reveals that various DL-based brain tumor classifications can be used. The performance of these techniques is of particular interest to scholars and practitioners. The variation among these techniques can be accounted for through understanding differences in the data augmentation techniques, preprocessing techniques, data sets utilization, use of custom-designed vs. pre-trained DL, and optional use of ROI segmentation before classification. For example, openly accessible contrast-enhanced T1-weighted brain tumor MRI scans [63] were utilized in the research. The pituitary, glioma, and meningioma brain tumor types were contained in their data sets. Also, vertical flipping and 90-degree rotation were used to augment datasets in the images. Resizing and normalization were taken as the preprocessing techniques, while coronal, sagittal, and axial were the three types of anatomical illustrations being made in their study. A custom CNN model was utilized while the F1-score (average of 94.94%), re-call (95.07%), precision (average 94.81%), accuracy (average of 95.4%), specificity, and sensitivity scores were used for performance evaluation of the model. The sensitivity was re-ported as 98.4% for pituitary, 96.2% for glioma, and while lowest of 89.8% for meningioma.

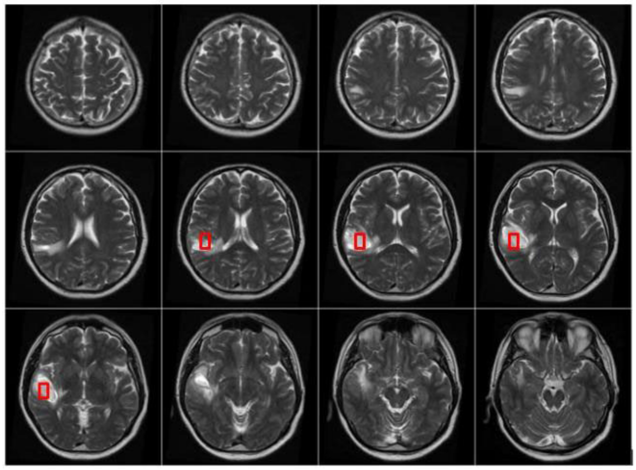

FIGURE 1. Normalized MRI showing different tumors.

V. BRAIN TUMOR CLASSIFICATION THROUGH DEEP LEARNING

In contrast to tumors in other parts of the body, human brain biopsy is not generally acquired before the surgery [66]. To acquire a precise diagnosis and prevent a medical process and subjectivity, a suitable diagnostics tool for the segmentation and classification of tumors from MRI images would be required to be developed [67]. In this regard, the development of novel technologies such as artificial learning and machine learning greatly impacts the medical field as they have offered significant support for medical imaging. Figure 1 shows the different images of brain tumors.

Several automated learning methods have been found applicable in MRI processing during the classification and segmentation of images that can assist radiologists with decisive insights. A special level of expertise is needed for brain tumor classification in the supervised approaches extraction of optimal features is needed, and choice has to be made about selection techniques. Hence, despite the massive potential associated with this method [64], these limitations cease to exist. So, in recent times, scholars have paid sufficient attention to unsupervised approaches [12] for their automatic feature generation capability with a decrease in error rate and excellent performance.

In numerous studies, models of deep learning (DL) have arisen as potentially applicable methods for image analysis in the medical field, including functions such as seg-mentation [68], reconstruction [69], and classification [12]. In [16] introduced a novel architecture for brain tumors based on

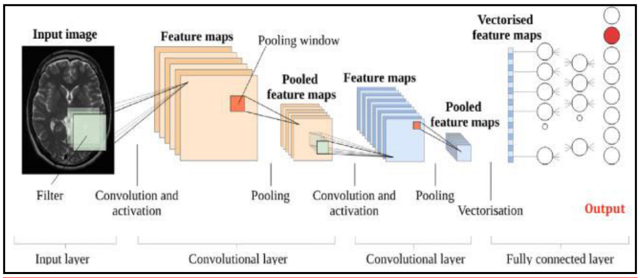

FIGURE 2. **CNN architecture.**

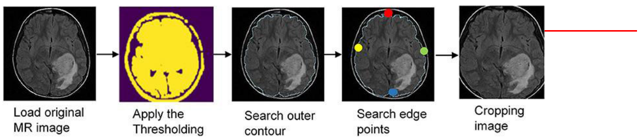

FIGURE 3. **Preprocessing steps.**

a convolutional neural network (CNN) con-ducting classification using three tumor types. Brain tumor classification was done through a new convolutional neural network (CNN) architecture by utilizing three tumor types in the study. Such models are based on simply developed networks with a previously pre-trained network that can be tested through weighted images. Four current methods were used for the evaluation of the overall model in their study. Two tenfold cross-validation methods and databases were combined in these methods. An augmented image database was utilized to assess the model's overall ability in their study. A convolutional neural network (CNN) is a widely used deep learning model for carrying out brain tumor classification. The adoption of these networks has introduced efficient results and improvements. Figure 2 shows the architecture of CNN model.

In the study of [70], a complete three-dimensional deep neural network (3D CNN) which was completely automatic and very efficient, was introduced. It had the tendency to classify glioma brain tumors into high-grade glioma (HGG) and low-grade glioma (LGG) by volumetric T1-Gado MR sequence. Their model merged Contextual information in global and local contexts while reducing their weights. As the new preprocessing technique was introduced, adaptive contrast enhancement and normalization of intensity were accomplished for MRI data. The influence of proposed data augmentation and preprocessing was further subjected to evaluation in terms of its accuracy in classifying data. A well-established benchmark of Barts has been identified for the evaluation of such results for authenticating the feature generation capability of the proposed architecture. The model of [70] outperforms others who followed a similar line of research. The overall accuracy of 96.49% has been established so far in the unsupervised and supervised models. Figure 3 shows the steps involved in data preprocessing.

Another prominent contribution lies in the work of [71], who came up with another model with the potential of automatic segmentation for segmenting MRI images in brain tumor diagnosis. Among the pipelined approaches toward machine learning mechanisms, convolutional neural networks (CNNs) hold a particularly special place in literature for approaching complex biological phenomena such as those in synapses (connections) and neurons (called nodes).

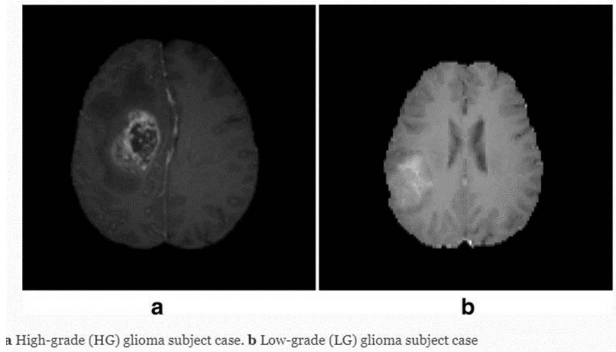

FIGURE 4. **Glioma subject cases in brain tumor.**

Based on structural multimodal magnetic resonance images (MRIs), [72] classified brain tumors and achieved greater consistency in generating accurate predictions. These authors proposed a three-dimensional context-aware deep learning for considering the uncertainty of the tumor area in MRI image sub-zones for performing tumor classification. Then, on the tumor classification, they appealed to a conventional 3D CNN for reaching the subtype of the tumor. They carried out survival prediction using a hybrid of machine and deep learning mechanisms. The Multimodal Brain Tu-mor Segmentation Challenge 2019 data set was subjected to proposed approaches for predicting overall survival chances as tumor segmentation was conducted. Robust segmentation was achieved through this model, and the classification took second place the classification results took second place.

In [71] researcher evaluated the constituent of CNNs for the classification of brain tumors by initiating an investigation with an understanding of CNNs and executed a review of the current state of the art for regulating an illustrative pipeline. They further transverse a novel field of radionics for further investigation with respect to CNN that facilitated quantitative structures of brain tumors such as textures and shapes of signal in-tensities for forecasting clinical results such as survival or general response to therapies. Robust segmentation and survival anticipation were also proposed through the con-text-aware neural network application by [72]. Figure 4 shows the glioma subject cases of brain tumor.

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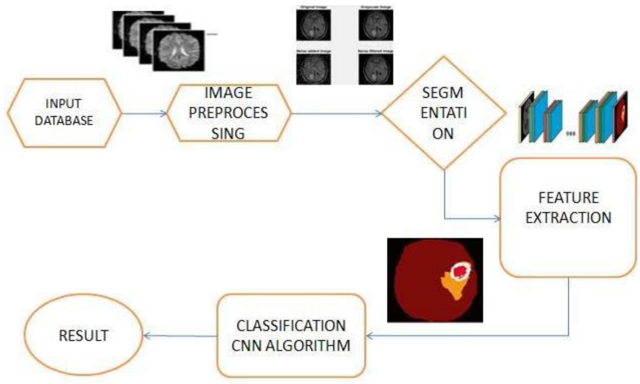

FIGURE 5. **CNN-based tumor classification.**

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Another study [74] proposed a BrainMRNet as a novel convolution neural network for classifying brain tumors. Attention modules provide the foundations for architecture, and a residual network accompanies a hyper-column technique. BrainMRNets preprocessing would start the model, and then augmented attention models were allocated for every image. After the selection of important areas in the MR image, CNN layers transfer it one after the other. A hyperactive column depicts the BrainMRNet model created through an indispensable technique in convolution layers. Array structure on every last layer carries the extracted features from each layer of the brain. The goal was to choose the most efficient and powerful features among all features contained within the array with 96.05% of success in classification achieved through the BrainMRNet model.

Neutrosophy co-evolution neural network (NS-CNN) was used in the research of [73] to develop a novel hybrid model that aimed at the classification of the tumor area from images of the brain as malignant and benign. A well-established maximum fuzzy-sure entropy (NS-EMFSE) method using a neutrosophy set was applied to segment MRI images. The k-nearest neighbors (KNN) classifiers and support vector machine (SVM) were used to classify and segment the brain image. Their results showed that excellent performance is portrayed with a variety of classifiers.

Another hybrid approach was taken by [75] for MR image utilization in brain tumor classification. On the basis of Resnet50 architecture, they developed a CNN model, and they took the last layer of the model out as eight layers were added. A high level of accuracy was achieved through this model. Results were obtained with InceptionV3, Densenet201, Resnet50, Alexnet, and GoogleNet models.

For MRI sequences, a Discrete wavelet transforms (DWT) fusion model was created by [76] through the use of CNN for brain classification. They presented a hybrid of four textures and structural information in MRI sequences (FLAIR, T1C, T1, T2). A fusion process was developed as Daubechies wavelet kernel was combined with DWT for producing a more detailed information view of the examined brain tumor. For feeding the presented CNN model, these authors used a thresholding method that could classify the tumor region from non-tumor regions.

Another DL-based brain tumor classification study was conducted by [82], who came up with a classification approach taken through automated multi-model classification, and five phases were introduced for the process. Once phases related to preprocessing and deep learning extraction were completed, two already trained CNN titled VGG16 and VGG19 were utilized to extract features, after which an extreme learning machine (ELM) was combined with correntropy-based joint learning to produce intended features. They reported an accuracy of 98.7%, showing promising performance of the multimodal classification approach.

Another automated model using CNN was introduced by [99] to produce results for brain tumor classification. Instead of relying on explicit features, the recognition of worthy information is carried out to train data for classification. These authors used the dice coefficient as a performance parameter to show the effectiveness of the model. However, in most of the literature, accuracy and other parameters have been utilized for performance measurement.

To improve the performance and reduce the computational complexity of conventional deep CNN, [81] proposed a novel model for the classification of the abnormal tumor. To reduce the number of amendments in parameters, favorable modifications were introduced in the training model. In the completely connected layers, the weight amendment procedure was left out by these scholars to safely reduce the

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Paper searching Algorithm technique from research databases
Procedure Paper TOPIC (Brain Tumor Analysis Using Deep Learning: A Comprehensive Survey)
Research databases ➡ MDPI, Google Scholar, PubMed, IEEE Xplore, ScienceDirect
Published year between 2018-2022 (Few are old as per research demand)
N ➡ 5                                  ❖ Number of research databases
I ➡ 1                                  ❖ Starting value
For N>=I
    Search keyword: classification, segmentation, machinelearning, braintumor, deeplearning
    If Year belong searchyear And searchlink belong searchdatabase then
        Search (classification And segmentation And machineleaning And braintumor And deeplearing)
    end if
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    If Papers >= 0
      Papers
      Inclusion_criteria ➡ IC1, IC2, ..., ICn
      Exclusin_criteria ➡ EC1, EC2, ..., ECn
End procedure
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FIGURE 6. Literature searching criteria.

computational complexity in the model. High accuracy was observed for the modified model in the study.

Authors have considered various parameters for drawing the effectiveness of their proposed models against the previous ones. In this regard, accuracy, specificity, and sensitivity have been widely utilized, while some scholars utilized Dice similarity, F1-Scores, recall ability and many other parameters to justify their models' performance. Table 1 presents an overview of the recently published literature on the classification of tumors through deep learning while comparing the performance of implemented approaches by these authors.

VI. METHODOLOGY

In this survey-based research, authors surveyed peer-reviewed work between 2018 and 2020 that was published by Web of Science and Scopus indexed journals. Survey aimed to evaluate the current state of the art on machine learning and deep learning-based classification models for classifying brain tumor regions from non-tumor regions in the brain. For this survey, an extensive review was conducted across major databases that included: MDPI, Google Scholar, PubMed, Science Direct and IEEE Xplore Digital Library. The search criteria included machine learning, deep learning, tumor classification, brain tumor classification and Deep Learning classification of brain tumor.

A set of inclusion and exclusion criteria was established for the selection of research papers from the above-mentioned databases. Inclusion criteria stated that the paper must be peer reviewed, it should be on brain MRR images and paper is from WOS and Scopus indexed journal. Exclusion criteria included case study papers, MSC, PhD papers, fewer or no citations and studies with techniques other than MRI and duplicate studies across multiple databases. Figure 6 shows the searching criteria for literature.

VII. DISCUSSION

This study offers an extensive examination of methodologies utilized for the segmentation and classification of brain tumors. A comprehensive range of both traditional machine learning and deep learning-based techniques are covered, accompanied by quantitative evaluations of their performance. Within traditional image segmentation approaches, including region growing and unsupervised machine learning, the paper identifies pertinent methods for brain tumor segmentation (as presented in Table 1). One of the earliest strategies, region growing, grapples with noise, suboptimal image quality, and seed point selection challenges. The application of automatic seed point selection via optimization techniques and AI-driven alternatives is explored to surmount these limitations. However, the efficacy of these measures diminishes when confronted with tumors dispersed widely across the brain. The subsequent wave of segmentation techniques, categorized as part of the second generation, centers around shallow unsupervised machine learning. Notably, methodologies such as fuzzy c-means and k-means clustering, designed to categorize pixels into multiple classes, are detailed.

Nevertheless, these methods remain noise-sensitive, thus motivating endeavors to bolster performance by integrating supplementary data and adopting adaptive centroid selection. The inherent complexity of delineating between normal tissue and brain tumors poses a formidable hurdle for both conventional and clustering-centric segmentation methods. The study highlights pixel-level classification-oriented segmentation techniques, which leverage traditional supervised machine learning approaches. These techniques often involve the intricate feature engineering process, wherein tumor-specific attributes are extracted to effectively train the model. Moreover, subsequent post-processing techniques are employed to refine the outcomes of supervised machine learning segmentation to enhance the final results.

In medical image analysis, classification and segmentation have been known among the major challenging tasks. A precise explanation of the affected region in the brain makes brain tumor classification the center of attention for practitioners and scholars in this area. A review of past studies reveals that successful detection of tumor region plays a pivotal role in improved treatment outcomes. The current state of the art promises immense potential through automation of the brain tumor classification as it can result in higher clarity of patient's state with the diagnosis while assisting in planning treatments and outcomes. With the application of various approaches, inevitable progress has been achieved in the automation of brain tumor classification. However, the pursuit of an entirely automated system is not without challenges when it comes to its complete adoption in the medical arena.

Previous studies and surveys [16], [17], [18], [19], [20], [21], [22] on various approaches toward brain tumor segmentation and classification revealed that automated models using deep learning models have superior performance as compared to the region growing and conventional machine learning mechanisms. So, this survey dedicated itself to the review of the current state of the art on automated

TABLE 1. Overview summary of existing techniques.

Ref.	Year	Brain Tumor Type	Classifier Model	Preprocessing Techniques	Sensitivity	Specificity	Accuracy	Other Parameters (Recall, Precision, Dice similarity coefficient, F1 score)
[57]	2021		Multiscale CNN	Pituitary, Glioma and Meningioma	-	-	97.3%	
[75]	2020	Gliomas	RF classifier	Intensity normalization/contrast enhancement	-	-	96.49%	-
[76]	2020	Gliomas	CNN-based classifier.	filter methods				Dice Coefficient: 0.821, 0.895, and 0.835 for ET, WT, and TC0.732-0.905
[77]	2020	-	Custom CNN model	Oligodendroglioma, Astrocytoma, Glioblastoma	-	-	Up to 98.14%	-
[78]	2019	Benign Tumors and Malign Tumors	CNN + SVM, CNN + KNN	filter methods	93.75 ± 0.62, 91.25 ± 1.25	92.5 ± 1.87, 83.75 ± 2.5	93.1 ± 1.25, 87.5 ± 1.87	-
[79]	2020	-	CNN (AlexNet, GoogleNet, VGG-16)		96.0%	96.08%	96.05%.	-
[80]	2020	Glioma	Resnet50 Densenet201, Googlenet and Inception V3, Alexnet models	-	94.7	100	97.2%	-
[82]	2022	Glioma, Meningioma, Pituitary Tumor	quantum variational classifier (QVR), min-max fuzzy classifier	-	-	-	98.8% - 99.7%	F1-score 0.91, Recall 0.94 and 0.88
[83]	2022		hierarchical deep-learning neural network (HieDNN)	SG denoising based	-	-	44.20%, 29.97% and 20.44%	-
[87]	2020	Grade II & III	VGG16	Normalization, resizing, padding, cropping,	87 %	92%	89%	-

TABLE 1. *(Continued.)* **Overview summary of existing techniques.**

[90]	2022	FLAIR, T1, T2, And T1CE	ResNet101 pretrained model	Normalization and Conversion	92.5%-96.7%		94.4%	-
[91]	2022		CNN based	-	98%	98.5%	98.97%	F1-score 97%
[92]	2022	Glioma	Support Vector Machine (SVM)	-	-	-	95.83% 96.19% for HGG type, 95.46% for the LGG t	-
[93]	2022	Meningioma, Glioma and Pituitary	Inception resnetV2	Binary-based boundary box detection			97.89%	Precision
[94]	2022	Glioma	DL model with IGWT technique	GBF filtering technique		99.45	98.3 %	F-score 98.36, Recall 98.4, Jaccard Index 96.78, Dice Coefficient 98. 36
[95]	2022	Glioma	ResNet50	randomly rotating augmentation and scaling augmentation		0.837		Recall 0.769, Precision 0.833, F1-score 0.80
[96]	2022	-	SoftMax classifier	scalable range-based adaptive bilateral filter (SCRAB) and noise reduction	87.5, 96 and 75	99.9 ,99.54 and 99.5	95.23, 98.5 and 93%	
[98]	2021	Class 1: Pituitary, Glioma, Meningioma, Metastatic, and Normal Class 2: Grade II, III & IV	Custom CNN model	-	-	-	92.66%, 98.14%	-
[99]	2021	HGG & LGG	Pre-trained DenseNet201	Pituitary, Glioma and Meningioma	-	-	99.8%, 99.3%	-
[100]	2018	-	Custom CNN model	Pituitary, Glioma and Meningioma	-	-	84.19%	-

TABLE 1. *(Continued.)* **Overview summary of existing techniques.**

[101]	2020	DWT	CNN	Pituitary, Glioma and Meningioma	-	-	96.15%,	F1-score 96.97%, PR 94.12%, RE 100%
[103]	2021		DDIRNet 6	Pituitary, Glioma and Meningioma			99.69%,	F1-score 99.4%, PR 99.6%, RE 99.4%,
[104]	2019	-	G-ResNet	Pituitary, Glioma and Meningioma	-	-	95%	-

classification techniques for brain tumor MRI to produce an inclusive picture of the most recent and worthy of adoption models proposed in this area. The powerful learning ability of deep learning mechanisms has been reviewed for their performance, and Table 1 of the study compares them. Furthermore, the categorization and classification of the methods have been presented before moving toward reviewing deep learning-based models on brain tumor classification. It has been established that deep learning-based models exceed expectation compared to the rest of the available approaches.

A review of past literature shows that it has been divided based on approaches taken toward classifying brain tumors. However, an inclusive review of the current state of the art highlights the effectiveness of automated deep learning-based models for offering precise insights to guide the treatment projections of brain tumor patients. Convolutional Neural Network has emerged as a powerful tool for image processing. It has been long adopted in tumor diagnosis, serving as a special kind of artificial neural network capable of recognizing and processing images at the pixel level. Convolution is a mathematical operation used by CNN that replaces simple matrix multiplication in at slightest one of its layers [64]. In the analysis of medical images, CNN deep networks have been widely recognized for their immense potential. However, the computational cost expense hinders clinical practitioners' adoption [102].

In brain tumor classification, many contributions came to the horizon in the past two decades, and the number is expected to grow even further. Advocates of computer efficiency and user supervision have been highlighted as huge aspects in practitioners' acceptance of classification models. However, despite the momentous de-elopements, a gap remains in practice due to a lack of association between academia and clinicians. Most practitioners still rely on manual estimates of tumors despite the availability of numerous models. In the developments made for unsupervised learning mechanisms, promising performance was proven by scholars throughout. It suggests that by bringing advanced deep learning models together for their classification potential and high potential in diagnosing brain tumors, one can begin to convince its adoption by clinicians. A summary showing the number of surveyed on the brain tumor segmentation is shown in Figure 7.

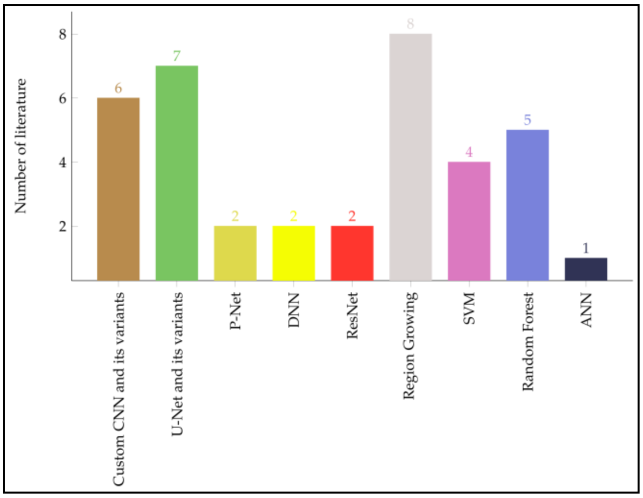

FIGURE 7. Brain tumor segmentation techniques survey.

VIII. CONCLUSION

Brain tumor classification from MRI images is a challenging and complex task as a high level of accuracy is in demand to provide the best insights for clinicians. It can be concluded from this research that despite the barrier to its adoption, Deep learning-based classification methods show a promising future in diagnosing and treating brain tumors. Recent developments in this area are recorded in this study, and outcomes in precise classification are evaluated. A gap remains in developing standard procedures to incorporate the potential of deep learning-based models in the diagnostic procedures carried out in real cases. Furthermore, there is a huge gap in the current literature regarding identifying security challenges posed to the computer systems during the classification of tumors from Brain MRI and the potential of tempered results through malicious intents.

Future researchers can work on the cost and resource optimization for CNN networks to encourage their widespread adoption in the medical field. Furthermore, they can work on developing standards for preprocessing techniques and improving the overall architecture.

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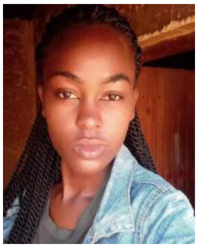
AYESHA YOUNIS was born in Faisalabad, Pakistan. She received the first M.Sc. degree in computer engineering from the University of Agriculture Faisalabad, in 2017, and the master's degree in signal and information processing from the Tianjin University of Technology and Education, Tianjin, China, in 2020. She is currently pursuing the Ph.D. degree with the School of Microelectronics, Tianjin University, Tianjin. Her research interests include biomedical signal processing, image processing, and medical image processing.

QIANG LI received the B.E. and M.E. degrees from the School of Information Engineering, Taiyuan University of Technology, Taiyuan, China, in 1997 and 2000, respectively, and the Ph.D. degree from the School of Electronic Information Engineering, Tianjin University, Tianjin, China, in 2003. He is currently a Professor with the School of Microelectronics, Tianjin University. His research interests include intelligent signal processing and AI system design.

MUDASSAR KHALID received the B.Sc. degree in electrical engineering from COMSATS University, Pakistan, and the M.Sc. degree in information and communication engineering from Northwestern Polytechnical University, China. He is currently a Research Assistant with Chulalongkorn University, Thailand.



BEATRICE CLEMENCE received the bachelor's degree in computer science (BCS) from the Institute of Accountancy Arusha, Tanzania, and the M.Eng. degree in applied computer technology from the Tianjin University of Technology and Education, China. She's currently a Research Assistant with Tianjin University of Technology and Education.

MOHAMMED JAJERE ADAMU (Member, IEEE) received the B.Eng. degree in computer engineering from the University of Maiduguri, Nigeria, in 2012, and the M.Eng. degree in signal and information processing from the Tianjin University of Technology and Education, China, in 2017. He is currently pursuing the Ph.D. degree with Tianjin University, China. His current research interests include signal and medical image processing and antenna design and analysis for industrial/medical applications.