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SURVEY

Brain Tumor Classification and Detection Based DL Models: A Systematic Review

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ABSTRACT In recent years, the realms of computer vision and deep learning have ushered in transformative changes across various domains. Among these, deep learning stands out for its remarkable capacity to handle vast datasets, revolutionizing numerous fields, including the biomedical sector. In particular, its prowess has been harnessed in the realm of brain tumor identification through MRI scans, yielding impressive results. This research project is dedicated to conducting an exhaustive exploration of existing endeavors in the domain of brain tumor identification and classification via MRI scans. This endeavor is poised to be of profound value to researchers looking to leverage their deep learning expertise in the realm of brain tumor detection and categorization. The initial phase involves an overview of prior studies that have employed deep learning for categorising and detecting brain tumors. Subsequently, a meticulous analysis of deep learning studies proposed in research publications spanning (2019 to 2022) is presented in tabular form. The conclusion section comprehensively assesses the merits and demerits inherent in deep neural networks. The insights gleaned from this study promise to equip future researchers with a holistic perspective on current research trends and a nuanced understanding of the effectiveness of diverse deep learning methodologies. It is our fervent belief that this research will significantly advance the understanding of brain tumors and their detection methodologies.

INDEX TERMS Cancer, tumor classification, features extraction, tumor detection, tumor segmentation.

I. INTRODUCTION

The world has witnessed a remarkable transformation in various domains in recent years, thanks to the remarkable advancements in computer vision and deep learning. The ability of deep learning models to handle vast amounts of data has yielded extraordinary outcomes in numerous fields, particularly in the biomedical domain. One area where deep learning has demonstrated significant potential and impact is the identification and categorization of brain tumors using magnetic resonance imaging (MRI) scans. The application of deep learning algorithms in this context has shown impressive results, offering great promise for efficient prognosis and improved patient outcomes [1]. The major goal of this research project is to conduct a comprehensive study on the diagnosis and classification of brain tumors using MRI data. The insights gained from this research will be particularly beneficial for researchers interested in leveraging

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their deep learning expertise for detecting and classifying brain tumors. Deep neural networks, the backbone of deep learning, have exhibited both advantages and disadvantages in the context of brain tumor detection and classification. Understanding these aspects is crucial for researchers seeking to leverage deep learning in this domain effectively. By objectively assessing deep neural network characteristics, such as their capacity to uncover subtle patterns from complex MRI data, researchers can harness the potential of these models to achieve accurate and efficient brain tumor detection. Additionally, comprehending the limitations of deep neural networks, such as their sensitivity to noisy or insufficient training data, can guide future research efforts and highlight areas for improvement.By providing an overview of previous studies and analysing the deep learning algorithms proposed in research publications between 2019 and 2022, this study aims to offer a comprehensive understanding of the efficacy of various deep learning methodologies in this domain [2]. To commence this investigation, it is essential to explore the earlier studies that have employed deep learning techniques for categorizing and detecting brain tumors. These studies have paved the way for novel approaches and have significantly contributed to developing advanced methodologies in the field. By examining the methods, data sets, and results of these studies, they can gain valuable insights into the progression of deep learning-based brain tumor detection and classification [3].

The subsequent phase of this research involves subjecting the deep learning algorithms proposed in the selected research publications to a detailed analysis [4]. This analysis aims to compare the various algorithms, highlighting their strengths, limitations, and performance metrics. Through this process, they aim to identify trends, patterns, and areas of improvement in deep learning methodologies for brain tumor identification and categorization. Deep neural networks, the backbone of deep learning, have exhibited both advantages and disadvantages in the context of brain tumor detection and classification. Understanding these aspects is crucial for researchers seeking to leverage deep learning in this domain effectively. By objectively assessing deep neural network characteristics, such as their capacity to uncover subtle patterns from complex MRI data, researchers can harness the potential of these models to achieve accurate and efficient brain tumor detection. Additionally, comprehending the limitations of deep neural networks, such as their sensitivity to noisy or insufficient training data, can guide future research efforts and highlight areas for improvement. The findings of this study hold significant potential for researchers and practitioners in the field of brain tumor detection and classification. The comprehensive comparison of current research methodologies will enable them to gain a holistic view of the advancements in the field and understand the efficacy of different deep learning approaches. Moreover, the insights gained from this study will contribute to the overall understanding of brain tumors and aid in developing more effective diagnostic tools and treatment strategies [5]. In conclusion, the emergence of computer vision and deep learning has revolutionized numerous fields, including the biomedical domain. The detection and classification of brain tumors using MRI scans have witnessed remarkable advancements through the application of deep learning algorithms. This research project aims to thoroughly investigate the existing work in this domain, analysing the deep learning methodologies proposed in research publications between 2019 and 2022. By examining these methodologies and evaluating their advantages and disadvantages, this study seeks to enhance the understanding of brain tumors and facilitate further advancements in the field. The findings of this research will empower researchers to make informed decisions regarding deep learning techniques for brain tumor identification and categorization, ultimately leading to improved prognosis and patient care.

II. MRI

Magnetic Resonance Imaging (MRI) assumes a paramount role as the principal imaging modality within the sphere of brain tumor detection and classification, leveraging advanced deep learning techniques. MRI provides detailed and high-resolution images of the brain, enabling the visualization of tumor morphology and characteristics [6]. The non-invasive nature of MRI makes it a preferred choice for imaging brain tumors, as it does not involve exposure to ionizing radiation. MRI scans capture multi-dimensional information, including T1-weighted, T2-weighted, and contrast-enhanced sequences, which provide valuable insights into the tumor's location, size, shape, and internal composition. These multimodal imaging data provide a complete imaging of the tumor and aid in the precise detection and categorization of brain cancers. The use of MRI in conjunction with deep learning algorithms enables the automated analysis and extraction of significant characteristics from imaging datasets, allowing for the development of robust and reliable models for brain tumor detection and classification. Integrating MRI with deep learning techniques offers tremendous potential in advancing our understanding of brain tumors and improving patient care in neuro-oncology [7].

III. BRAIN TUMOR CLASSIFICATION

The ability of sophisticated computer vision and deep learning approaches to manage massive volumes of data and extract high-level features from complex MRI scans contributes to their effectiveness in brain tumor classification. Deep learning models, like as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have transformed the field by automatically developing discriminative representations of brain tumors using their hierarchical designs. These models are trained on huge datasets of labeled MRI scans to capture local and global spatial information and temporal connections in successive images. By learning from varied samples, deep learning systems can generalize and accurately classify brain cancers based on their specific imaging patterns [8].

One of the key advantages of deep learning in brain tumor classification is its ability to handle the inherent variability and complexity of tumor images. Brain tumors can exhibit diverse morphological and textural characteristics, making their classification a challenging task. However, deep learning models excel in learning complex patterns and can capture subtle imaging features that may be indicative of specific tumor types or malignancy grades. This capability allows for more precise and nuanced classification, enabling clinicians to make informed decisions regarding patient management and treatment planning [9].

The availability of high-quality, well-annotated datasets is crucial to the success of these models. Collecting and curating such datasets can be a time-consuming and resource-intensive task, particularly when considering the need for diverse tumor types and variations in imaging protocols. Additionally, deep learning models are susceptible to overfitting when trained on limited data, emphasizing the importance of robust data augmentation techniques and regularization strategies to ensure generalization to unseen cases [10]. Another difficulty is that deep learning models are difficult to interpret. Despite their outstanding effectiveness, these models are frequently referred to as ''black boxes'' due to the difficulties in comprehending the reasons behind their judgments. This lack of interpretability undermines clinical trust and adoption of these models. Efforts are being made to build explainable AI algorithms that can provide insights into the features and regions impacting classification results, allowing physicians to make more confident and educated recommendations.

IV. BRAIN TUMOR DETECTION

Deep learning brain tumor detection algorithms excel at understanding subtle patterns and extracting relevant characteristics from complex imaging data. These models can detect minor anomalies and distinguish them from normal brain tissue throughout training [11]. Deep learning algorithms can discover distinct imaging characteristics associated with several forms of brain cancers, including gliomas, meningiomas, and metastatic tumors, by utilizing vast datasets of labeled MRI scans. The success of deep learning-based brain tumor detection can be attributed to the hierarchical nature of these models. CNNs, for instance, utilize multiple layers of convolutional and pooling operations to learn features at different levels of abstraction progressively. This hierarchical approach allows the models to capture low-level features, such as edges and textures, and high-level features indicative of tumor presence. The combination of these learned features enables accurate detection and localization of brain tumors within MRI scans [12].

Furthermore, deep learning models can exploit MRI scans' spatial and contextual information to enhance detection performance. By analyzing the relationships between neighboring pixels or voxels, these models can identify spatial patterns specific to tumors. This spatial awareness is particularly valuable in distinguishing tumors from normal brain structures and reducing false positive or false negative detections. Additionally, deep learning models can leverage the temporal information provided by sequential MRI scans, enabling the detection of dynamic changes in tumor growth and progression [13].

Interpretability constitutes a pivotal facet necessitating contemplation within the realm of deep learning-driven tumor detection. Notwithstanding their commendable performance, deep learning models frequently acquire the moniker of ''black boxes'' owing to the intricacies associated with comprehending the intrinsic decision-making mechanisms. This paucity of transparency might pose an impediment to their embrace within clinical settings, given that clinicians demand lucidity and elucidations for the resultant prognostications. Vigorous endeavors are currently underway to cultivate elucidatory AI methodologies capable of affording discernment into the constituent attributes and domains wielding influence over detection determinations. In doing so, this endeavor seeks to bolster confidence levels and expedite seamless assimilation into clinical workflows [14].

V. HUMAN BRAIN

Before the development of a method vital in improving the process of detection relating to human brain abnormalities, it is important to develop a complete insight into the structure of the normal human brain by illustrating the ROI. The provision of the description is helpful in decreasing the likely misses combined with the provision of incorrect detection. References [15] and [16] asserts that the brain is recognised as the most complicated human organ as it provides thought, feeling, memory, action and experience to a person with respect to internal and external environment. The brain's weight is about 1.4 kilograms and includes 100 billion nerve cells, also called neurons. Moreover. The grey matter (GM), cerebrospinal fluid (CSF), and white matter (WM) of the human brain are further divided as shown in Figure 1.

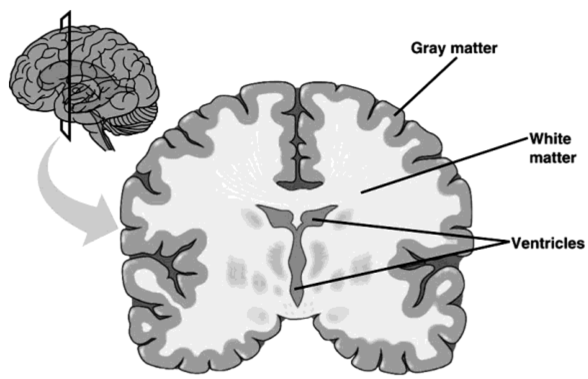

FIGURE 1. Grey matter and white matter brain tissues.

References [15] and [17] assert that the human brain includes the CSF, that incorporates different elements such as glucose, salts, enzymes and white blood cells. As shown in Figure 2, this CSF refers to a fluid element that circulates across the spinal cord and brain. The CSF moves through various channels and functions as a shield for the brain along with the spine from damage [18]. Identifies the presence of the meninges tissue that envelops the spinal cord and the brain through the existing membrane.

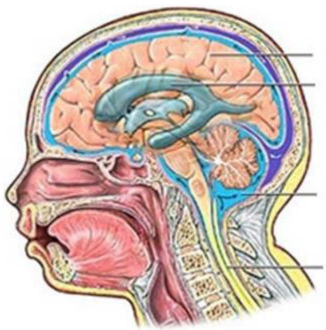

FIGURE 2. Normal CSF circulation in the brain.

The brain's anatomical composition comprises the cerebellum, cerebrum, and the brain stem [15], [19], [20]. The cerebrum is the brain's largest component and controls sensation, locomotion, and conscious thought. It is divided into 2 major parts, including the right and left cerebral hemispheres, wherein the individual halves control the body's opposite parts. These individual halves are divided into 4 parts: the occipital, parietal, temporal, and frontal lobes. The cerebellum is the other half which controls the motor capabilities including posture, walking, balance, and general motor management. The cerebellum is a region of the brain that is related to the brain stems. A thin external cortex of internal WM, GM, and small deep-mated GM masses make up the cerebrum and cerebellum.

VI. METHODOLOGY

This research project's methodology employs a systematic approach to analyzing existing work on brain tumor diagnosis and categorization using deep learning algorithms. The major goal is to provide a thorough understanding of the efficacy of various deep learning approaches in this domain and aid future research in this subject.

To begin with, an exhaustive literature study is undertaken to find relevant research publications focusing on applying deep learning methodologies for brain tumor identification and categorization utilizing MRIs spanning the years 2019 to 2022. The selection criteria include studies that propose novel deep learning algorithms, utilize large-scale datasets, and report significant results. The identified publications serve as the basis for further analysis and comparison. Next, the selected research publications are carefully examined to extract essential information regarding the methodologies employed. This includes details about the deep learning models used, such as CNNs or RNNs, the architecture configurations, and the training strategies. Additionally, information about the datasets. This thorough analysis provides insights into the diversity and characteristics of the methodologies employed in the field.

Subsequently, a comparative analysis is performed to evaluate the performance of the deep learning algorithms proposed in the selected research publications. The examination entails a comprehensive evaluation of diverse performance metrics, including but not limited to accuracy, sensitivity, specificity, and the area under the receiver operating characteristic curve (AUC-ROC). These quantitative measures serve to facilitate a rigorous appraisal of the algorithms' efficacy in the precise identification and classification of cerebral neoplasms. The comparative analysis aims to identify trends, patterns, and potential areas for improvement in deep learning methodologies for brain tumor identification.

In addition, the benefits and drawbacks of deep learning approaches are thoroughly evaluated. The strengths of these approaches are identified and underlined, such as their ability to handle enormous volumes of data and discover complicated patterns. Furthermore, the constraints and challenges are extensively explored, such as the requirement for large and well-annotated datasets, potential overfitting, and a lack of interpretability. Understanding these factors provides a comprehensive understanding of deep learning approaches for brain tumor detection and classification.

VII. DATASETS

The availability and use of various and well-curated MRI datasets is critical for brain tumor diagnosis and classification utilizing deep learning approaches. These datasets include a wide variety of MR images collected from patients with various forms of brain tumors, including tumor grades, sizes, and locations. T1-weighted, T2-weighted, and contrast-enhanced sequences are commonly included in MRI datasets, providing comprehensive imaging information. Additionally, the datasets may incorporate multi-modal imaging data, such as MRI (MRI), which offer complementary insights into tumor characteristics and behavior. In order to train and evaluate deep learning models, annotated and validated ground truth labels for tumor presence, kind, and other relevant clinical information must be included. The MRI datasets' quality and diversity significantly influence the developed models' performance and generalisation, as they enable the models to learn from a representative range of tumor variations. Therefore, meticulous attention is given to dataset acquisition, preprocessing, and augmentation techniques to ensure the reliability and integrity of the MRI datasets, ultimately enhancing the accuracy and effectiveness of the deep learning algorithms for brain tumor identification and classification, some of datasets have been by the pervious references are shown in Table 1.

VIII. METRICS OF PERFORMANCE

Performance metrics are essential tools that provide evidence of the effectiveness and reliability of specific algorithms or models. These metrics offer valuable insights into the performance and capabilities of a given algorithm, allowing for a comprehensive evaluation of its working [42]. Table 2 presents a comprehensive list of the performance

TABLE 1. Datasets that are publicly available.

Source	Names of Datasets	Data used
(The IBSR Dataset from the year 2021 stands)	IBSR	Ye, Fangyan, et al.[21]
(isles 2021)	ISLES	Mudda et al.[12]
(Johnson and Becker 2021)	THE ENTIRE BRAIN ATLAS	Kaur and Doegar.[22]
(oasis, 2021)	OASIS	Anilkumar and Rajesh. [23]
(Rider et al. 2021)	RIDER	–
(Radiopedia et al 2021)	RADIOPEDIA	Gopalan and Remya, [24]
(TCIA 2021)	TCIA	Amin, Javaria, et al.[25] Bhanothu, Yakub et al.[26]
(figshare, 2021)	FIGSHARE CJDATA	Al-Tamimi and Sulong,[27] Çinar and Yildirim,[28] Raja and Viswasa,[23] Özyurt, Fatih et al.[29] Islam, Rafiqul, et al.[30]
(Brain Tumor, 2021)	BRATS (2012– 2019)	Sahoo et al..[31]; Kalaiselvi et al..[32]; Kurup et al.[33] Togaçar et al.[34]; Amin et al.[35] Anilkumar and Rajesh [36]
(ATLAS OF CANCER GENOMICS, 2006)	ATLAS OF CANCER GENOMICS	Ozyurt et al.[29] Amin et al.[25] Sharif et al.[37] Nazir et al.[38]
(kaggle, 2021)	KAGGLE	Togaçar, Mesut et al.[39] Bhanothu, Yakub et al.[26] Begum, S. Salma [40] Han, Woo-Sup et al.[41],

metrics commonly employed in the literature. Each metric is accompanied by its corresponding formula and functionality, providing a deeper understanding of its purpose and significance. It is important to note that only the metrics that hold significance for classification tasks are included, ensuring a focused and relevant analysis of the algorithm's performance. Table 2 shows These performance metrics serve as valuable benchmarks for assessing the accuracy and efficacy of different algorithms in classifying brain tumors and contribute to a thorough evaluation of their capabilities.

Figure 3 provides an extensive overview of the evolution of deep learning models over four years, reflecting the progressive advancements in this field through meticulous research and development. The figure delineates a chronological representation, showcasing the trajectory of deep learning models across different epochs of research.

IX. RELATED WORKS

Deep neural networks have revolutionized the process of feature extraction and selection by leveraging their inherent self-learning capabilities. Over time, a wide range of deep

TABLE 2. Metrics of measurement.

Metrics of measurement	Formula	Functionality/ Definition
Specificity	TN / (TN + FP)	The quotient to accurately predicted negative observations in relation for the entirety of negative observations within their corresponding class.
Sensitivity/Recall	TP / (TP + FN)	The proportion to accurately predicted positive instances relative for the total positive instances within their respective class.
Precision	TP / (TP + FP)	Precision, in its precise definition, encapsulates the ratio of correctly foreseen positive instances to the entirety of anticipated positive occurrences.
Accuracy	(TP + TN) / (TP + TN + FP + FN)	It represents the aggregate count of accurately predicted observations expressed as a percentage of the whole.
Loss of Training /Validation	$[\text{Actual- Predicted}]^2$	Training loss signifies to the degree of error when processing of training dataset, while the validation loss indicates the error encountered when the trained network is applied to the validation dataset.
Learning rate		It determines how frequently the learnt ideas of the neural network are updated.
Temporal Performance		The cumulative duration encompassed by the program or model in its execution upon a well-trained computing system.
PPV	TP/(TP + FP)	It represents the ratio of authentic positive outcomes within the positive results.
[False Rejection Rate (FRR) / Missed Alarms]	FRR = FN/(FN + TP)	It denotes the percentage of positive observations erroneously rejected or forecasted as negatives.
FAR (False Acceptance Rate)/ False Positive/False Alarm Rate	FAR = FP/(FP + TN) TA = Total Number of Attempts FA = Number of False Acceptances	The proportion of negative data that is projected mistakenly as positive.
Equal Error Rate (EER) F1 Score	FAR = FRR 2*TP/ (2*TP + FP + FN)	FAR = FRR. The weighted average of precision and recall determines the F1 Score.
AUC (Area Under the ROC Curve)		The ROC curve's area under the curve (AUC) is a metric elucidating the model's capacity to discriminate between disparate classes effectively. In the

TABLE 2. ***(Continued.)*** **Metrics of measurement.**

	assessment of test instances, an AUC value of 1 is regarded as the pinnacle of optimality, signifying flawless discriminatory performance.
Validation by comparison	Cross-validation stands as a resampling methodology strategically employed to appraise the performance of machine learning models within the constraints of a finite data sample.

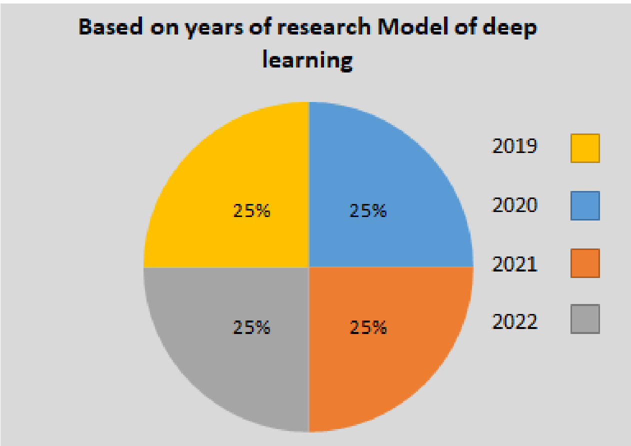

FIGURE 3. **Research per years based deep learning model.**

learning models, varying in complexity, have been developed and showcased remarkable outcomes in medical imaging, including the analysis of MRIs for brain tumor detection [43] This study evaluates the performance of deep learning algorithms in classifying brain tumors using MRI data by critically reviewing over 80 academic publications. Deep learning algorithms have more than doubled in use for brain tumor classification, with further growth expected due to the benefits they give in terms of data processing and automation. A comprehensive evaluation of research publications published in the last four years is provided, with a focus on the use of DL models with brain tumor detection and classification using MRIs. However, the review was organized during the year, with a brief summary of each work to enhance academics' comprehension and information gain. The annual research is detailed in full, including the deep learning models employed, the datasets used, and details on pre-processing techniques and data augmentation.

A. STUDIES PUBLISHED IN 2019

In 2019, a significant amount of technical research was conducted, focusing on applying DL as the primary element in proposed algorithms. In our study, they specifically handpicked a selection of articles from 2019 that prominently utilized Deep Learning techniques. The purpose of this chart is to present a comprehensive overview of these research works, highlighting their key findings and contributions. By focusing on articles from this specific year, they aim to provide valuable insights into the advancements and developments made in the field of Deep Learning during that time period [44]. The investigators adeptly harnessed compression methodologies to enhance the precision and velocity of Convolutional Neural Networks (CNNs) when applied to the intricate task of brain MRI classification. Antecedent to the classification stage, they ingeniously integrated a novel preprocessing procedure. The methodology initiates its workflow by employing a Probabilistic Neural Network (PNN) to detect the Region of Interest (typically corresponding to brain tissue regions). Subsequently, two backpropagation neural networks are judiciously deployed to compress the identified ROI. Ultimately, the CNN is enlisted to classify the condensed image data. In the pursuit of comparative analysis, data for three distinct optimizer types were methodically amassed, attainment of a 90% accuracy rate. The investigation of the density of the RESNET34 architecture in terms of efficiency is a subject of scrutiny in [45]. The architects of G-RESNET embarked on the development of this novel framework by adopting the fundamental deep RESNET34 paradigm. This innovative technique replaces the conventional flattening layer with a global max pooling layer, and a bespoke loss function is meticulously crafted. A series of discrete evaluations were undertaken to discern the distinct impacts exerted by the global max pooling layer and the redefined loss function on classification accuracy. Ultimately, through a compelling experiment in feature fusion, the fusion for both low-level, high-level features culminated in the emergence of G-RESNET—an ingenious network featuring an optimized loss function and a harmonious blend of features, thus achieving an impressive 95% accuracy rate [46] Introduced an innovative approach for the detection and classification of tumors into either malignant or benign categories. Their method employs a score-level fusion technique, which amalgamates the output vectors from pre-trained models, specifically Alexnet and Googlenet, to categorize the segmented tumor region accurately. The raw MRIs undergo meticulous preprocessing, involving linear and logarithmic transformations. Subsequently, the tumors are delineated through a combination of thresholding and morphological procedures, effectively segmenting the region of interest. This segmented area is then utilized to perform a high or low-grade classification, with the aid of the BRATS dataset, facilitating the accurate characterization of tumors [47]. The study's authors introduced the Faster R-CNN approach as an advanced method for precisely identifying and classifying MRIs depicting brain tumors. The images are initially fed into a simple CNN, which generates a convolutional feature map, which is then converted into area recommendations and molded into a feature vector by the ROI pooling layer. Finally, a faster R-CNN is used to classify this ROI feature vector. SVM was also utilized to generate as much separation between classes as feasible, allowing the system to correctly categorize the images. Their algorithm was 95% accurate. The authors of this study [48] shed light on the profound significance of multimodalities within brain MRI imaging. Their work elucidates that the amalgamation of multimodal data engenders outcomes of heightened accuracy. Within this investigation, the authors employed the BRATS 2018 dataset. The images underwent preliminary processing encompassing grey-level normalization and contrast rectification. Additionally, conventional methodologies were harnessed to complement the data. Subsequent to this stage, the pre-processed images from all four modalities were input into a 3D CNN for classification. To expedite convergence, the authors employed immediate normalization techniques. Notably, a refined loss function was also incorporated. As evidenced by the conclusive findings, the model attained a dice score of 92%, achieved through the amalgamation of insights gleaned from multiple modalities.

The central concept revolved around treating 3D MRIs as though they were 2D slices and subsequently employing them as input sequences [49]. In pursuit of this objective, deep learning techniques were harnessed to engender three distinctive comparative models: DENSEnet-RNN, DENSEnet-LSTM, and DENSEnet-DENSEnet. The inaugural model leveraged DENSEnet for feature extraction, while the second model enlisted a Recurrent Neural Network (RNN) as its data classifier. Notably, the feature extractor within the second model remained DENSEnet, but the classification task was executed by Long Short-Term Memory (LSTM). The third model followed a similar paradigm, employing DENSEnet both as a feature extractor and classifier. these three models' accuracy rates are 87%, 91%, and 92%. The authors of this study [50] employed the standard CNN for brain tumor MRI categorization. The program divides the images into three groups. The images must first undergo pre-processing. After scaling, each image is histogram equalized and smoothed with a Gaussian filter. The pre-processed images are then fed into a 5-layer CNN architecture. According to the final data, the suggested technique achieves an accuracy of 94.39 percent and an average precision of 93.33%. The authors' graphs of training accuracy and loss viewed encouraging results compared to numerous state-of-the-art models [51]. Investigate the use of the freshly built Capsule network's efficiency in their research. Convcaps is a novel variant of the Capsulenet paradigm introduced by the authors. Notably, the network takes two inputs: the tumor image and the segmented tumor class. So, the new loss function is also added to optimize sub-network performance thoroughly. The researchers do six tests with diverse inputs to evaluate the model's performance comprehensively. When compared to other state-of-the-art models, the obtained results show that the improved algorithm achieves the greatest accuracy of 93%.

Reference [52] we've developed a cutting-edge Deep Learning methodology designed exclusively for brain tumor segmentation and classification. The first part of their suggested method is thoroughly examining Convolutional Neural Networks (CNNs) with three separate classifiers: the SoftMax layer, the Radial Basis Function, and Decision Trees. Surprisingly, the SoftMax layer proved to be the most effective for classifier, to get highest accuracy. The model integrates easily with the central clustering process to retrieve crucial information. These collected features are then sent into the proposed CNN algorithm, which is supplemented by a fully linked SoftMax layer to aid classification. The results of rigorous experimentation reveal the amazing capability of the proposed methodology, with an accuracy rate of 96%. Deep Learning has emerged as a remarkable tool for processing vast volumes of substantial data, surpassing numerous conventional methodologies. In [53], pioneers unveiled a groundbreaking web-based Deep Learning software, crafted in Python and harnessed within the Keras framework, meticulously tailored for the analysis of T1-weighted contrast-enhanced images. This software initiates its operation by subjecting the input images to an array of preprocessing techniques, encompassing rotations, rescaling, and truncations. Furthermore, it exhibits adaptability in accommodating diverse image formats, including jpeg, jpg, and png. Ultimately, the software undertakes the classification of the input MRI dataset through the adept utilization of Convolutional Neural Networks (CNNs), achieving high efficiency in discerning three distinct categories: meningioma, glioma, and pituitary tumors. The trial findings substantiate a 95% accuracy rate across all three classes.

Convolutional Neural Networks (CNNs) exhibit several drawbacks, with one of the most crucial being their failure to consider the spatial relationship between objects and their surroundings. However, a groundbreaking solution to this predicament has been put forth in the form of the CAPSNET model, recently introduced by [54]. This model introduces a dilated capsule network, serving as an extension to the traditional CNN. Notably, the dilated CAPSNET architecture addresses the limitation by replacing the pooling layer found in conventional CNN architectures with a novel ''routing by agreement'' layer. Prior to the algorithm's execution, So the method meticulously for pre-processes of images to ensure their compatibility and suitability. The dilated CAPSNET incorporates dilated convolutions within its convolutional layers to enhance image resolution. Remarkably, the proposed technique has yielded a remarkable accuracy rate of 95% based on the obtained results [55]. Uses a standard convolutional neural network (CNN) with eight layers to categorize brain MRI pictures as tumor or non-tumor. The algorithm starts by classifying the images using the CNN architecture that is being used. Further segmentation techniques are used if a tumor is discovered in an image. To begin, a global thresholding approach is used to binarize the picture, followed by the watershed algorithm and subsequent morphological procedures that extract the tumor from the segmented regions. Furthermore, the algorithm quantifies the tumor area. The acquired results demonstrate the efficacy of the suggested method, with a 96% accuracy rate. The central constraint of the convolutional neural network (CNN) resides in its voracious appetite for an extensive corpus of data. This resource may not be conveniently available across diverse research domains. A recent inquiry by [56] embarked upon an inventive trajectory in a concerted effort to surmount this challenge. The scholars introduced an innovative stratagem that harnesses the potency of Generative Adversarial Networks (GANs) operating in the arenas of noise-to-image and image-to-image conversion for the purpose of data augmentation. This enterprise unfolds in two distinct stages. In its inception, the study employs a scheme of progressively expanding GANs, orchestrating the creation of authentic brain imagery endowed with stochastic attributes. Subsequently, in the ensuing phase, the Multimodal UNsupervised Image-to-image Translation (MUNIT) procedure intervenes to further refine the synthetically generated images, thereby elevating their fidelity. Post the augmentation endeavor, the classification task falls under the purview of the robust RESNET-50 model, renowned for its discriminative prowess. Diverse model iterations were instantiated, each characterized by nuances in the quantity of training and testing images enlisted. The outcome of this empirical endeavor prominently underscores the preeminence of the advanced data augmentation strategy over conventional methodologies accuracy rate of 96%. The outcomes given in the [57] study demonstrate the efficacy of Faster R-CNN as a capable tool for improving tumor detection precision. A pre-trained Alexnet was used in conjunction with a Region Proposal Network (RPN) in the suggested technique. Initially, the model performs exclusive dataset preparation. Following that, the ALEXNET convolutional feature map was used as input to RPN, making it easier to compute Regions of Interest (ROIs). The F-RCNN undergoes training employing these Regions of Interest (ROIs). The authors adeptly employed end-to-end with four-stage training methodologies in the proposed design. The outcomes revealed a 97% accuracy rate attained through the end-to-end training process [58]. Present a novel adaptation of the CAPSNET model, designed to perform the classification of brain MRIs into three distinct categories based on their respective types. It is posited that conventional Convolutional Neural Networks (CNNs) inherently lack the capacity to effectively integrate spatial relationship information pertaining to the tumor's immediate surroundings. To surmount this inherent limitation, our proposed CAPSNET architecture ingeniously incorporates the contextual information surrounding the tumor in conjunction with the core image data. The initial stage involves feeding the MRIs into the CAPSNET model for the classification task. thereby enhancing the classification process proposed approach accuracy of 88%.

Authors in [59] introduced an intriguing approach for brain MRI classification, advocating the utilization of the pre-trained ALEXNET architecture, provided that appropriate features are supplied to it. The process begins with feature extraction using the curvelet transform and the Gray Level Co-Occurrence Matrix (GLCM). The curvelet transform provides multiscale geometric analysis in the frequency domain, whereas the GLCM derives texture-based features using a statistical technique. Following that, all of the retrieved features are concatenated and fed into the ALEXNET model as input, the model attains a remarkable accuracy of 98% when evaluated on the given dataset [10]. Introduced an enhanced iteration of the Googlenet model, customizing it to create a fully autonomous system endowed with the capacity to categorize brain tumors into three distinct classifications: glioma, meningioma, and pituitary tumors. Our innovative approach adeptly confronts the intrinsic challenge of limited datasets by harnessing advanced transfer learning techniques. Initially, they tailored the Googlenet model to align with the requisites of a multi-class classification problem, followed by meticulous fine-tuning on the training dataset. Subsequently, this transfer-learned and finely adjusted model is deployed to explicitly classify tumor types. employ a fivefold cross-validation scheme at the patient level across the dataset. The results of experiments accuracy rate of 98% [60]. The authors have introduced an improved iteration of two prominent convolutional neural network (CNN) models, specifically, ALEXNET and VGG-16. Their proposed methodology initiates with a meticulous image preprocessing phase, encompassing noise elimination and resizing operations, aimed at ensuring the highest possible data quality. Following this preparatory step, the pre-processed images are harnessed for the training of both models. In addition, a user-friendly Graphical User Interface (GUI) has been meticulously crafted to facilitate result visualization during the classification phase. It is noteworthy that both models have undergone enhancements through the augmentation of both feature maps with convolutional layers. For each architectural modification, the authors have introduced three distinct model variations. Notably, the conclusive outcomes demonstrate that Model No. 3 of ALEXNET has attained an impressive accuracy rate of 96%, while Model No. 1 of VGG-16 has emerged as the frontrunner, surpassing the others with an outstanding accuracy rate of 98% [9]. They conducted an empirical investigation wherein they harnessed five distinct CNN models to classify tumors into three distinct categories: meningioma, glioma, and pituitary tumor. The depth of the five models was only altered, but the hyperparameters remained intact. The researchers concentrated solely on changing the architectural depth of the five models and thoroughly recorded the results. With two concealed layers, was the most effective of the models tested. This model achieved a tumor classification accuracy of 98% [61]. An advanced CNN architecture was proposed to precisely classify two distinct brains MRI datasets The initial dataset was classified into three groups: meningioma, glioma, and pituitary tumors, while the second dataset was assigned tumor grades (grades 2, 3, 4). To ensure optimal performance, the methodology initiated with image pre-processing, involving resizing, followed by data augmentation to enhance generalizability and mitigate overfitting. Additionally, two dropout layers were incorporated within a 16-layer model to alleviate overfitting concerns further. The experiments were independently conducted on the two datasets. The outcomes remarkably demonstrated an accuracy rate of 96% for the first dataset and an accuracy rate of 98% for the second. Figure 4 describe the utilization of deep learning algorithms. In 2019, became prevalent across various industries. These algorithms reshaped numerous sectors, showcasing their transformative potential. Their widespread adoption marked a significant trend in technological advancements during that year.

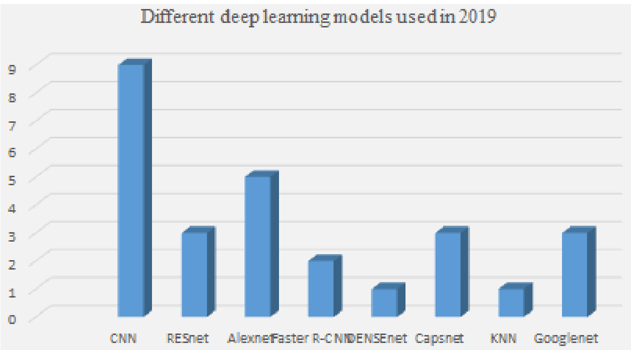

FIGURE 4. Deep learning algorithms utilization in 2019.

B. STUDIES PUBLISHED IN 2020

In the year 2020, a multitude of technical studies were undertaken, and our evaluation process will commence by examining the research papers published during this period. Specifically, our focus will be on a selection of publications from the year 2020, and a comprehensive review of these papers is provided in this section. By delving into the findings and methodologies of these chosen studies, they aim to gain valuable insights into the advancements and contributions made in the field of research during that particular year [32]. The principal distinction among the six CNN models lies in the depth of their architectural layers. Alongside the dropout layer, two more CNN models incorporate halting criteria and batch normalization, while the last two models operate without these elements. For training, the BRATS 2013 Dataset serves as the foundational resource, while the World Brain Atlas (WBA) is reserved for the testing phase, The accuracy rate 96%. Reference [62] carried out additional research. The proposed solution involves changes to the original model's pre-processing and classification steps. The method, employs median filtering during the pre-processing stage that was successfully reduces noise through maintaining of edges. Furthermore, within the convolution layer, the model employs a modified both SoftMax with loss function rather than the sigmoid function, which is inefficient when dealing with multi-class classification problems. The tumor is segmented in the final stage using a combination of the watershed algorithm and morphological operations. Finally, the findings show substantial accomplishments, with the model achieving 97% accuracy while significantly lowering processing time [33]. Utilizing a dataset comprising 3064 images as its foundational substrate, this study integrates two fundamental pre-processing techniques, namely rotation and patch extraction, as traditional methods for augmenting data quality and quantity. Following these enhancements, the images undergo a downsizing transformation, rescaled to dimensions of 28 × 28 to streamline model complexity. The evaluation of the data augmentation's effectiveness and the subsequent classification of brain tumor images into three distinct categories—meningioma, glioma, and pituitary tumor—are carried out utilizing a capsule-net architecture. Notably,enesis convolutional neural network, denominated BrainMRNET. This model cwith a omprises three principal components. The foremost element is the Convolution Bloof the ck Attention Module (CBAM), affording the network the capability to acquire both channel-specific and spatial information. In the subsequent phase, the utilization of residual blocks augments the network's capacity to glean salient features, with the Hyper Column technique intervening prior to the fully-connected layer. Whatever, the technique concatenates for feature maps stemming from all convolutional layers, endowing the model with enhanced generalization and classification efficacy. The BrainMRNet model achieved classification accuracy 96.05%. The authors of [26], To detect and classify brain tumors, Employ a faster R-CNN. The mathematical foundation for the construction for FasterR-CNN was employs the VGG-16 architecture. The tumor area was accurately marked using the region proposal network. The Figshare data set was utilized to divide the data into three categories. The suggested technique improves Mean Average Precision by 77.60 % for all three classes, according to the results [30]. Focuses on using multi-level segmentation to efficiently extract and classify brain tumor features from MRI data. After pre-processing the MRI imaging data, the authors used thresholding, watershed approach, and morphological operation for segmentation. CNN is utilized to extract features to identify tumor images as malignant or non-cancerous, followed by K-SVM. Overall, the suggested method has an accuracy of 87.4 % [37]. The authors proffer a duo of network architectures, delineating one for segmentation and another for classification purposes. They embarked on fine-tuning the pre-trained inception V3 model, employing the BRATS training dataset for this purpose. The infusion of profound attributes ensued through by incorporating Rotated Local Binary Patterns (DRLBP), artfully concatenated in a rudimentary array-based fashion. Subsequently, Particle Swarm Optimization (PSO) was harnessed to curtail the feature set. The outcomes gleaned from assessments conducted on the BRATS dataset reveal, an accuracy of 92%. In medical iData augmentation plays a critical role in imaging, where datasets are scarce, data augmentation search at emphasizes necessity of data augmentation [41]. The authors enriched the

BRATS-2016 dataset by incorporating the features extracted from "Progressively Growing Generative Adversarial Networks (PG-GANs)", employing them in tandem with RESNET-50 for the purpose of efficacious tumor identification. A comparative analysis was conducted between conventional data augmentation methods and the PG-GAN-based approach. The findings underscored the efficacy of employing a hybrid augmentation strategy, accuracy rate of 91%. The authors of [23] developed a system that uses Deep Learning and statistical modeling to distinguish between images with and without malignancies. The authors use a non-local mean filter to preprocess the images, effectively reducing noise. Following that, the segmentation is carried out using the Bayesian Fuzzy C-means algorithm. Information-theoretic metrics, including wavelet packet Tsallis entropy (WPTE) and scattering transformations (ST), serve as the means for feature extraction in this context. Subsequently, a classification process is executed employing a Deep Autoencoder (DAE) grounded in the Jaya optimization algorithm (JOA) in conjunction with SoftMax regression. The outcomes accuracy rate of 98.5% [25]. Emphasizes the relevance of MRI pre-processing and segmentation as a prerequisite for putting them into a deep learning system. Their method entails sharpening the MRIs, followed by median filtering to smooth out any noise effectively. The tumor region is then separated using region growth to provide input to a finely calibrated stacked sparse autoencoder (SSAE) model. The BRATS dataset from 2012, 2013, 2014, and 2015 was then used to train and test this model. According to the data, the proposed technique enhanced accuracy and sensitivity. In the work of [28], an advanced iteration of RESnet50 is introduced, offering enhanced performance in the classification of brain MRI into tumor and non-tumor categories. The original RESnet50 architecture is augmented with the addition of eight layers, and the model is subsequently trained on an MRI dataset sourced from Kaggle. Notably, a comparative analysis is conducted, pitting the results of the proposed system against those of prominent CNN architectures such as Googlenet, Alexnet, and DENSEnet. The findings reveal that the proposed approach achieves a superior accuracy of 97% when contrasted with other Deep Learning models. The study conducted by [64] leverage the importance of data pre-processing to enhance classification accuracy and reduce error rates. The primary focus lies in implementing data augmentation techniques, which serve to improve generalizability and mitigate the issue of gradient vanishing. Initially, the data undergoes resizing and center cropping to minimize the presence of background information that offers no significant contribution to the classification task. Subsequently, a total of seven augmentation techniques are applied to expand the dataset, thereby mitigating overfitting concerns. Finally, the augmented dataset comprising MRI scans is utilized as input for training and testing the Resnet50 architecture. Notably, the achieved results demonstrate accuracy of 98% [35]. Leveraging the innovative dwt (discrete wavelet transform) technology, introduced a novel methodology for amalgamating four distinct MRI modalities into a singular MRI. This cutting-edge approach facilitates the creation of a fused MRI sequence tailored to each patient. Subsequently, employing the ensemble of five MRI datasets, which incorporates the fused MRI sequences, a Convolutional Neural Network (CNN) model is meticulously trained. The findings emanate as a testament to the utility of the fused images, as they manifestly contribute to a notable enhancement in classification accuracy. Reference [29] offers a novel hybrid approach termed SR-FCM-CNN. To begin, the authors employ an SR CNN network for pre-processing. This network effectively converts low-resolution images to high-resolution images, allowing FCM segmentation. To boost the classifier's generalization capabilities, the pictures are complemented with rotation and zooming techniques. The Squeeze-net architecture is then utilized to extract features, which are then classified with the ELM approach. The results obtained demonstrate a 98% accuracy [36]. Explore the significance of transfer learning as a critical component for overcoming the issues associated with limited datasets. The researchers suggest a sophisticated method that uses VGGnet as its basic design. This method capitalizes on a pre-trained VGGnet while conducting meticulous block-wise fine-tuning across six discrete blocks, each characterized by a distinct layer's number. Then, the authors craft six distinct models by independently adjusting various blocks within each model, thereafter subjecting the outcomes to rigorous analysis. The investigation draws upon two publicly accessible datasets, namely BRATS and CE-MRI. classification accuracies reaching 97.28% and 98.69% on the respective datasets [65]. Explores the attributes of the Kaggle MRI brain tumor dataset through the utilization of a renowned CNN architecture. So, the CNN model receives the MRI as input, subsequently subjecting it to a series of operations, including pre-processing, segmentation, and feature extraction using CNN. The resulting output is then classified as either depicting a tumorous or non-tumorous MRI. The authors have developed a Graphical User Interface (GUI) to facilitate efficient interaction with the algorithm. The devised algorithm exhibits accuracy range of 90-99% when evaluated on the Kaggle dataset. The authors of [66] have employed the Haar wavelet transform as a means to extract salient features from brain MRIs. This transformative process partitions the input image into two discernible sets of attributes: approximation and detail coefficients. Subsequently, the authors harnessed the approximation coefficients to facilitate the training of a deep Convolutional Network (CNN) model. In this inquiry, the CNN approach produces a substantial accuracy of 99.3%, whereas the SVM case achieves a considerable accuracy of 98% [40]. Introducing a cutting edge and highly effective algorithm created for classifying and segmenting brain tumors. This algorithm is built on a foundation of features. Initially our proposed approach involves preprocessing MRIs to eliminate any noise artifacts. Then they extract attributes using both the run length texture features with the GLCM matrix. To further optimize our algorithms performance, they utilize the Oppositional Gravitational Search Algorithm (OGSA), for dimensionality reduction enhancing the feature set. The refined feature set is then fed into a Recurrent Neural Network (RNN) for classification to determine whether the image represents a tumor or non-condition. In addition to classification our algorithm also focuses on segmenting the Region of Interest (ROI) within tumor images during a phase. It's worth noting that our proposed algorithm achieves a 96% accuracy rate, in classification [67]. Introduce an innovative algorithm, aptly named BRAINnet, designed specifically for MRI analysis. This algorithm exhibits remarkable efficiency in accurately detecting the presence of tumors. Moreover, in instances where tumors are detected, the second BRAINnet architecture proficiently classifies the tumor into its respective category through segmentation techniques. The outcomes of this study demonstrate accuracy rate of 98% for tumor detection and an even higher accuracy of 99% for tumor classification. Notably, these results are comparable to the performance achieved by state-of-the-art approaches in the field [68]. Employing a Convolutional Neural Network (CNN), this innovative methodology is dedicated to the classification of brain MRIs into discernible tumor and non-tumor categories. The research team has meticulously engineered a Graphical User Interface (GUI) for this system, facilitating the seamless integration of two distinct datasets, namely Kaggle and TCIA. To identify the most productive optimization technique, three disparate approaches are systematically applied and evaluated. accuracy rate of 98%, the adoption of RMSprop accelerates the algorithm's execution during both the testing and training phases, further underscoring its utility.

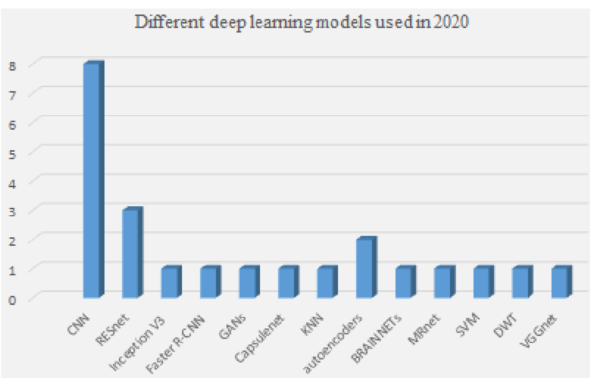

FIGURE 5. **Deep learning algorithms utilization in 2020.**

In 2020, the pervasive adoption of deep learning algorithms continued to drive innovation across diverse fields depicted in Figure 5.

C. STUDIES PUBLISHED IN 2021

During 2021, a significant amount of technical research was carried out, focusing on utilising Deep Learning as the primary tool in proposed methodologies. In our study, they carefully selected a subset of publications from 2021 that prominently employed Deep Learning techniques. These chosen publications serve as valuable sources for our analysis, as they provide insights into the advancements and innovative approaches developed within the field during that particular year. By examining the methodologies and outcomes presented in these selected papers, they aim to gain a comprehensive understanding of the role and effectiveness of Deep Learning in the context of the research conducted in 2021 [69]. To improve the accuracy of categorizing tissue as tumor or non-neoplastic, the suggested framework incorporates Discrete Cosine Transform (DCT), Convolutional Neural Network (CNN), and ResNet50 architecture. Before classification, the framework uses super-resolution to improve the resolution of MRIs. Experiments reveal that when utilized with super-resolution and the ResNet50 architecture, the DCT-CNN ResNet50 framework achieves an accuracy rate of 98.14% [70]. Utilizing the Unet architecture with ResNet50 as its foundational backbone, they achieved a remarkably high Intersection over Union (IoU) score of 0.9504 in the context of segmentation. The incorporation of preprocessing techniques and data augmentation strategies played a pivotal role in enhancing the classification accuracy. To classify brain tumors into distinct categories, they harnessed the power of evolutionary algorithms and leveraged reinforcement learning through transfer learning methodologies. In pursuing tumor categorization, they employed a diverse array of Convolutional Neural Network (CNN) models, including the MobileNet V2, Inception V3, ResNet50, DenseNet201, and NASNet. These models exhibited impressive accuracy levels of 91.8%, 92.8%, 92.9%, 93.1%, and an astonishing 99.6%, respectively, with NASNet emerging as the frontrunner in accuracy. Notably, they explored two transfer learning approaches, namely "freeze" and "fine-tune," to adeptly the extract critical features to get it from MRI slices. They employed a trifecta of architectural solutions for the complex task of multi-classifying brain tumors: NASNet, ResNet50-UNet.

In the initial phase of research reported in [71], embarked on the development of a sophisticated 3D convolutional neural network (CNN) architecture meticulously designed to address the task of brain tumor elimination. Subsequently, the resulting tumor elimination outputs were fed into a pretrained CNN model, serving as a proficient feature extraction tool. These extracted features underwent rigorous scrutiny through the application of a correlation-based selection approach, from which the most salient features were judiciously chosen. These meticulously selected features were further validated via a feed-forward neural network, culminating in the ultimate classification process. To put our methodology to the test and evaluate its effectiveness, they employed three distinct BraTS datasets from the years 2015, 2017, and 2018. The outcomes of experiments and validation efforts were notably promising, with classification accuracies of 98.32%, 96.97%, and 92.67% achieved for these respective datasets [72]. To improve the automatic segmentation process of the Convolutional Neural Network by introducing size variability (CNN). The UNET model is employed as a convolutional neural network-based encoder-decoder for pixel-wise tumorous slice categorization. A multi-inception-UNET model is proposed to improve the scalability of the UNET paradigm. The datasets from the Brain Tumor Segmentation Challenge (BRATS) have been used in several studies to demonstrate their validity. The BraTS 2015, 2017 and 2019 datasets had an accuracy of 91% for the whole tumor, the core tumor, and the augmenting tumor regions [73]. The testing of 16 distinct transfer learning models. Subsequently, the F1 Score, a metric harnessed in conjunction with state-of-the-art technologies, was introduced to precisely categorise brain malignancies depicted in MRIs. This classification methodology was anchored upon the utilization of a transfer learning-based model known as VGG-SCNet, denoting the VGG Stacked Classifier. The VGG-SCNet exhibited performance, boasting precision, recall, and F1 scores of 99.2%, 99.1%, and 99.2% [74]. Two databases, namely BRATS (2012, 2013, 2014, 2015) and ISLES-SISS 2015, were harnessed to train and assess the proposed model. This innovative approach pivots on a foundational framework characterized by a hybrid deep CNN and a deep watershed auto-encoder (CNN-DWA). The workflow unfolds in a meticulously orchestrated sequence, partitioned into six distinct phases. Firstly, it encompasses the introduction of MR images. Subsequently, the dataset undergoes preprocessing involving a suite of filter and morphology operations. The third phase entails the transformation of MR brain images into a matrix representation. The fourth phase is the pivotal application of the hybrid CNN-DWA model, which serves as the linchpin of this novel methodology. Following this, in the fifth phase, the model engages in the vital tasks of classifying and detecting brain tumors. The sixth and final phase assesses the model's performance, gauged through the derivation of five quantitative metrics. This pioneering hybrid CNN-DWA model has unveiled exceptional outcomes, accuracy 98% and a negligible loss validation score of 0. This hybrid model exudes a remarkable capability for precise tumor classification and identification [75]. Using MRIs, the proposed ensemble learning system identifies brain tumors and autoimmune disease lesions. The procedure includes pre-processing, feature extraction, feature selection, and classification. The tumor and lesion ROIs, Collewet normalization, and Lloyd-max quantization are all used during the pre-processing step. The base learner is an SVM classifier with majority voting that serves as the prediction model. The technique achieved 98.719% accuracy with 97.5% weighted sensitivity, 98.838% specificity, 98.011% precision, and 97.957% and 97.744% overall training and testing accuracy, respectively [76]. The model in question is an intricate deep convolutional neural network (CNN) meticulously engineered to predict and precisely segment brain tumors from MRI data. This formidable architecture boasts a substantial multitude of layers and parameters, its training grounded upon a substantial dataset consisting of 3929 MRI scans. Among these scans, 1373 featured tumors, while 2556 did not. Prior to feeding this data into the model for training, it underwent meticulous preprocessing and enrichment procedures. To gauge its efficacy, the model underwent a comprehensive evaluation utilizing an array of metrics, encompassing the Jaccard Index, DICE score, F1-score, accuracy, precision, and recall. it underwent a rigorous comparative analysis against two alternative models, namely UnetResNet-50 and Vanilla Unet, employing state-of-the-art methodologies. Based on the available data, the outcomes revealed that the proposed model, UnetResNext-50, is attaining an accuracy rate of 99.7% and DICE score of 95.73%. In [77] authors, scrutinized two segmentation approaches, namely a semi-automatic approach and two registration-based methodologies. These registration-based algorithms were designed to assess brain deformation post-craniotomy by leveraging pMRI and 3D iUS data. Both strategies harnessed the power of linear correlation within linear combination metrics and normalized gradient field metrics. Our evaluation encompassed a dataset consisting of 66 instances, encompassing B-mode and contrast-mode 3D-iUS data featuring metastatic and glioblastoma cases. The proposed approaches accuracy rate of 86.79%. A classifier for brain tumor classification based on a Gabor-modulated convolutional filter has been reported. The application of Gabor filter dynamics provides the capacity to handle spatial and directional variations [78]. Simply substituting standard convolutional filters with Gabor filters allows the architecture to learn comparatively smaller feature maps, reducing the need for network parameters. Added a few skip connections to our modulated CNN design without changing any network parameters. The accuracy is 98.68%. In [79], to identify anomalies within brain MR images, it is recommended to employ a novel architectural approach known as the Less Layered and Less Complex U-Net Model, abbreviated as LeU-Net. This model draws inspiration from the foundational principles of both Le-Net and U-Net but distinguishes itself in terms of its unique architectural and design characteristics. In this study, they propose the LeUNet, a deep learning model, and subject it to a comparative analysis against well-established CNN models, namely Le-Net, U-Net, and VGG-16.

However, our experimentation involves utilizing a comprehensive MR Dataset comprising both cropped and uncropped images. The evaluation of model performance across these datasets reveals compelling results. Specifically, the LeU-Net model attains an impressive overall accuracy of 98% when applied to cropped images and 94% when processing uncropped images. These findings underscore the LeUNet architecture's efficacy, particularly in anomaly detection within brain MR images, and signal its potential for advancing the field of medical image analysis [80]. A strategy for segmenting brain tumors in MRIs using a weighted fuzzy factor based on kernel metrics is proposed. To increase prediction accuracy, a deep autoencoder (DAE) is used in conjunction with the barnacle mating algorithm (BMOA) and random forest (RF) classifier. This paper proposes a deep-neural network topology for classifying brain MRIs that combines DAE and RF with a classification unit. BMOA and RF are used by the DAE to assess the segmented features. Using the suggested process in MATLAB, performance can be analyzed using currently accessible tools. So, the experimental results for the proposed method were reviewed and validated in MR brain images using quality analysis based on performance accuracy, sensitivity, and specificity. The accuracy is 95.84% [81]. The classification of distinct types of brain MRIs was performed using deep learning. The ResNet CNN architecture was discovered to have a mean overall accuracy of 99.06% for categorizing the kind of brain MRIs using a dataset of 10,000 images per class for training [82]. To classify brain tumors in MRI data, the model uses an ensemble strategy that combines three fine-tuned base learners (VGG16, Inception-V3, and ResNet50). It also includes two primary ensemble learners and a final ensemble model. The model was trained using images of three different types of brain malignancies as well as normal brain images, and the retuning procedure improves its accuracy [83]. Using YOLOv5 and FastAi, a subset of the BRATS 2018 dataset containing 1,992 brain MRI scans was employed for brain tumor diagnosis and classification. The YOLOv5 model had an accuracy of 85.95%, whereas the FastAi classification model had an accuracy of 95.78%. Both models are capable of detecting brain cancers [84]. The suggested DWAE model is a deep wavelet autoencoder that is used to classify brain MR images as normal or abnormal (tumor). It employs a high pass filter and a median filter to increase the quality of the output slices and a seed growth method based on 4-connected pixels to detect tumors. The model is trained and evaluated on 2500 MR brain pictures from multiple datasets and comprises two layers with 200 and 400 hidden units, respectively [85]. It is suggested to use fusion-based brain tumor segmentation and detection be used. To begin, a discrete wavelet transform (DWT) and a unique fusion rule were utilized to fuse the input image. The features of the grey-level co-occurrence matrix (GLCM) are extracted after the fusion operation. Using an Optimal Deep Neural Network (ODNN), classify the brain images as normal or pathological. To choose the best network weights for the DNN, the Spider Monkey Optimization (SMO) technique is used. Following categorization, the weighted k-means algorithm segments the brain tumor region from aberrant brain images. The performance of the proposed methodology is measured using sensitivity, specificity, and accuracy. The proposed method had the highest sensitivity of 94% [86]. Developed a cutting-edge classification and segmentation method for identifying brain tumors. The suggested method employs an adaptive fuzzy deep neural network with frog leap optimization to detect image normalcy and abnormality. Reduced errors lead to more accurate classification. The adaptive flying squirrel approach is then used to segment the erroneous image, and the size of the tumor is calculated to evaluate its severity. Have a 99.6% accuracy rate while categorizing [87]. Two DL networks, U-Net and U-Net with DenseNet, are proposed for brain tumour classification. The approach was tested on a database of 300 high-grade tumor cases and 200 normal cases, with data augmentation used to improve performance. When the performance of the proposed Dense Convolutional Network (DenseNet) architecture was compared to the U-Net design, it was discovered that the proposed DenseNet had an accuracy of 88.7% [88]. Meticulously crafted a deep network model by leveraging ResNet-50 architecture in tandem with a global average pooling strategy. In quest to evaluate the model's efficacy, they harnessed a dataset comprising 3064 brain magnetic resonance images depicting three distinct types of tumors.Through a rigorous performance analysis, meticulously scrutinized the model's competence, benchmarking it against its counterparts using essential performance metrics. with the model achieving a mean accuracy rate of 97.08%. The diagram presented in Figure 6 illustrates in 2021, deep learning algorithms were extensively deployed.

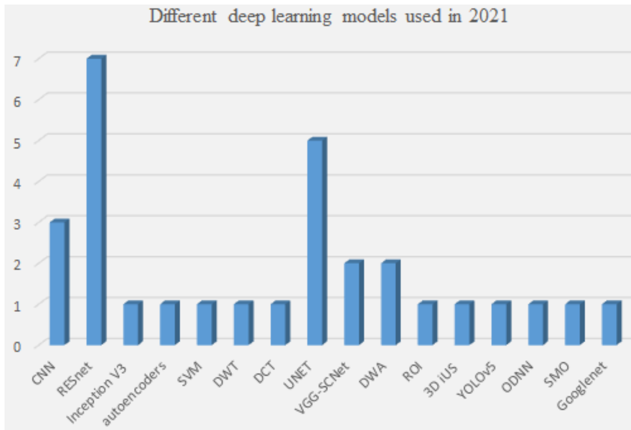

FIGURE 6. Deep learning algorithms utilization in 2021.

D. STUDIES PUBLISHED IN 2022

In the year 2022, extensive technical research was carried out, with a particular emphasis on utilizing Deep Learning as the primary tool in proposed methodologies. They carefully handpicked a selection of publications that focused on leveraging Deep Learning techniques for our analysis. This method serves as a comprehensive summary, encapsulating these studies' key findings and methodologies. By examining these chosen publications, they aim to gain valuable insights into the advancements and contributions made in the field of research during the year 2022. Through this summary, they aim to provide a comprehensive overview of the role and impact of Deep Learning in the context of the research conducted in that particular year [89]. The T1C modality MRI served as the foundational dataset for the creation of two distinct neural networks: a shallow convolutional neural network (SCNN) and a more complex VGG16 network. These networks underwent a rigorous evaluation, primarily focusing on metrics such as loss and accuracy. The knowledge gleaned from the deep learning models, along with the classification accuracy for three distinct tumor types, were amalgamated strategically to enhance the model's overall accuracy and provide comprehensive insights into the loss data. This fusion culminated in the development of an ensemble deep CNN model (EDCNN). Its ability to ameliorate accuracy in multiclass classification challenges was evident. The model is classification accuracy of 97.77%.

Reference [90] DLBTDC-MRI is an automated deep learning-based model for detecting and categorizing brain tumors. The methodology includes preprocessing, segmentation, feature extraction, and classification. Adaptive fuzzy filtering is used as a preprocessing strategy to minimize noise and improve the quality of MRI scans. Image segmentation utilizing chicken swarm optimization is performed to locate injured parts of the brain. A Residual Network is used to extract relevant feature vectors for brain cancer diagnosis, and a classifier is built by integrating DLBTDC-MRI with CSO. The model was tested using the BRATS 2015 dataset [91] M-SVM is utilised to classify brain tumours, identifying meningioma, glioma, and pituitary images. To identify the edges in the source image, the researchers used linear contrast stretching. Then, utilising transfer learning datasets from BraTS 2018 and Figshare datasets, a customised 17-layered deep neural network architecture was created for the segmentation of brain tumours, and a modified MobileNetV2 architecture was employed for feature extraction [92]. They present a pioneering methodology that involves the integration of an optimization-driven deep convolutional ResNet model with a novel evolutionary strategy. This strategic amalgamation is designed to intricately refine not only the architecture but also the hyperparameters of the deep ResNet network. Furthermore, they introduce an advanced iteration of the Ant Colony Optimization, denoted as IACO, which is inspired by the foundational principles of differential evolution strategies and multi-population operators. This innovative synergy of techniques heralds a promising advancement in the field of optimization-driven deep learning, offering a sophisticated framework for enhancing the performance of ResNet models. The empirical assessments conducted on this framework yielded compelling results. Proposed approach achieved an average accuracy rate of 0.98694, providing compelling evidence for the remarkable effectiveness of our IACO-ResNet methodology [93]. To segregate brain tumors from 2D MRI of the brain, a convolutional neural network algorithm is developed, which is then followed by classical classifiers and deep learning techniques. Various MRIs with varied tumor sizes, locations, shapes, and image intensities were obtained to train the model effectively. The SVM classifier was used, and its performance was compared to other activation methods (softmax, RMSProp, sigmoid, and so on). The proposed Python technique made use of TensorFlow and Keras. CNN has an accuracy rate of 99.74%.

Reference [94] for the purpose of classifying brain tumors, CNN classifies the brain image with four categories: no tumors, indicating that the particular MRI for the brain does not contain a meningioma, tumour, glioma, and pituitary tumour. This model achieves 99% accuracy and facilitates automated feature learning from brain MRIs. Dataset: Public Domain CCO licensed by Kaggle [95]. Presents a system that uses ADAS optimization and artificial intelligence algorithms to detect brain cancers on MRIs accurately. One of the most hazardous diseases for humans is one that this technology is designed to help doctors diagnose. Patient imaging data gathered from Vietnam's Bach Mai Hospital was utilised in the study. The suggested strategy consists of two basic steps. To remove extraneous components from brain MRIs without altering their information content, theyfirst suggest the normalisation method. Deep Convolutional Neural Networks are then used in the following stage, and they recommend using the ADAS optimization tool to create prediction models based on that normalised dataset. Data was gathered from Bach Mai Hospital with 94% accuracy [96]. Demonstrates a deep learning-based strategy for categorizing and diagnosing brain tumors using the cutting-edge object detection framework YOLO. The YOLOv5 is a cutting-edge deep learning object identification method that uses less processing resources than competing models. The Brats 2021 dataset from the RSNA-MICCAI brain tumor radio genomic categorization was used in this investigation. The RSNA-MICCAI brain tumor radio genomic competition dataset was labeled using the make sense artificial intelligence web tool for labeling dataset. The preprocessed data is then separated into training and testing sets for the model. The YOLOv5 model is 88% accurate [97]. Extract profound features from the Inceptionv3 model, utilizing them to distinguish between various brain tumor types, including glioma, meningioma, instances with no tumor, and pituitary tumors. The resultant Softmax score vector serves as input for the Quantum Variational Classifier (QVR), a pivotal component in our methodology. Subsequently, the Seg-network is employed to process the classified tumor images, enabling the precise delineation of the actual affected regions, thus facilitating the measurement of tumor severity levels. To rigorously evaluate our research, they conducted assessments on three diverse benchmark datasets: Kaggle, 2020-BRATS, and a collection of locally acquired images. proposed model its detection performance of 90% [98]. Examine the comparative efficacy of the VGG-16, ResNet-50, and Inception-v3 models in the automated prediction of brain tumor cells. Pre-trained models demonstrated their effectiveness, pre-trained models exhibit proficiency on a dataset comprising 233 MRI brain tumor images demonstrating their effectiveness. Leveraging the VGG-16 pre-trained convolutional neural network model for brain cancer detection, they intended to scrutinize the accuracy and reliability of our model's performance. The VGG-16 pretrained model yields results, concurrently elevating both training and validation accuracy metrics. The datasets employed in this study have been meticulously curated from the Kaggle Dataset repository [99]. The ‘‘(CNN Database Learning with Neighboring Network Limitation) CDBLNL’’ methodology represents a cutting-edge advancement in the sphere of medical image processing, specifically geared towards the classification of brain tumor images. In its pursuit of delivering dependable insights, this recommended system architecture is intricately designed, featuring a multilayer-based metadata learning framework seamlessly integrated with a CNN layer. The encoding strategy employed for an additional dimension is sparse, while a metadata-driven vector encoding approach is diligently employed. The construction of atoms pertaining to neighboring limits is rooted in a meticulously structured k-neighbored network, meticulously preserving the supervised data within a geometric context. This methodology has on two distinct datasets, namely BRATS and REMBRANDT, accuracy rate of 97.2%. Authors in [100], presented a modified U-Net structure based on residual networks, with periodic shuffling in the encoder part and sub-pixel convolution in the decoder section. On two benchmark datasets, including the 2017 and 2018 Brain Tumor Segmentation (BraTS) Challenge datasets, the proposed U-Net model achieved segmentation accuracies of 93.40% and 92.20%, respectively. Tumor subregions were further classified as tumor core (TC), total tumor (WT), and enhancing core (EC). [101] DeepTumorNet represents an innovative hybrid deep learning model meticulously designed to categorise three distinct types of brain tumors: glioma, meningioma, and pituitary tumors. At its core, this model leverages the foundational architecture of the CNN model, namely GoogLeNet. In the development of the hybrid DeepTumorNet approach, a deliberate modification was implemented, involving the removal of the final five levels of the GoogLeNet architecture. In their place, a sophisticated ensemble of fifteen additional layers was intricately woven into the model's structure. This augmentation was further complemented by the introduction of a leaky ReLU activation function within the feature map, enhancing the model's capacity to capture intricate patterns and nuances. The performance of the proposed model was rigorously assessed using a publicly available research dataset. These include accuracy rate of 99.67%, precision of 99.6%, flawless recall at 100%, and a robust F1 score of 99.66% [102]. Image enhancement techniques are adeptly applied to mitigate noise and refine aspects like image size, contrast, and brightness. Employ image segmentation strategies founded upon morphological operators. Next, they delveoped into feature extraction operations, encompassing dimensionality reduction and the judicious selection of features based on a fractal model. Finally, they enhance the feature set through segmentation, ultimately selecting the most optimal class via a sophisticated fuzzy deep convolutional neural network. The method proposed accuracy rate of 98.68%. To substantiate these findings, they conducted extensive experiments utilizing the BraTS dataset, which comprises magnetic resonance imaging data [103]. A convolutional autoencoder technique is used to categorise 3D MRIs of brain malignancies. Unenhanced Magnetic Resonance Imaging (MRI) requires pricy and intrusive contrast-enhancing treatments to be used for clinical diagnosis. MCTL can boost accuracy by 1.5%, making it easier to find small targets. This study can be used to improve the precision of brain tumour severity diagnosis using MRI Database REMBRANDT, among other medical imaging and diagnostic methods accuracy 94% [104]. Introducing a novel and innovative deep learning paradigm, they present the 3ACL model, which stands for Attention-Convolutional-Long Short-Term Memory (LSTM). This model is thoughtfully tailored to handle MRI data, and it distinguishes itself by seamlessly integrating attention, convolutional, and LSTM structures into a unified learning architecture. This achievement is realized through a holistic end-to-end learning strategy. The fully connected layer within the 3ACL model serves as a potent feature extractor, adept at capturing highly representative deep features. The feature collection is seamlessly channeled into a Support Vector Machine (SVM) for refined analysis. This is achieved by aggregating SVM prediction results from all image slices. In the evaluation phase, the proposed technique delivered 98.90% and 99.29% accuracy rates for the BRATS 2015 and 2018 datasets, respectively. These results underscore the effectiveness and promise of our 3ACL model in the realm of MRI data analysis [105]. To effectively categorise and detect brain tumor images, they employed a sophisticated convolutional neural network (CNN) as our foundation. Specifically, they fine-tuned the advanced EffcientNet-B0 base model by incorporating a set of meticulously designed additional layers. To enhance the visual quality of the images, they meticulously applied multiple filters, employing image enhancement techniques that significantly improved the overall picture quality. The empirical results speak volumes, underscoring the prowess of our fine-tuned state-of-the-art EffcientNet-B0. The overarching achievement of approach was a classification and detection accuracy rate of 98.87%. Noteworthy alternatives in our exploration included VGG16, InceptionV3, Xception, ResNet50, and InceptionResNetV2 as additional deep learning algorithms [106]. The detection and categorization of brain tumors are introduced using a novel generalised framework. For two distinct goals, the suggested framework utilised two different deep models. The first one transforms a small class-unbalanced dataset into a large balanced dataset using a neural variational generative model. The classifier, a convolutional model, is the second used to identify brain MRI tumours. The suggested framework performed equally well in terms of accuracy, precision, recall, and F1-score 96.88% [107]. Compare the ability of the ResNet50 network to identify brain tumors using various traditional data augmentation strategies. contains our technique based on major component analysis. The Image Net dataset was utilized to train the network trained from zeros via transfer-learning. Because of the inquiry, they were able to obtain an F1 detection score of 92.34%.

The diagram depicted in Figure 7 provides a visual representation showcasing the widespread deployment and extensive utilization of deep learning algorithms throughout 2022.

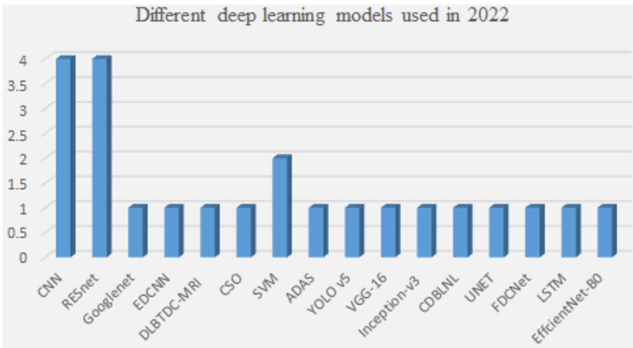

FIGURE 7. **Deep learning algorithms utilization in 2022.**

The suggested technique and learning transfer application resulted in the score utilizing the ResNet50 network. Furthermore, using a significance threshold of 0.05, it was discovered that the proposed strategy varies from the other traditional ways utilizing the Kruskal Wallis test statistic [108] Brain tumor classification utilizing a fully automated design. The proposed method employs the most effective deep learning characteristics for classifying FLAIR, T1, T2, and T1CE tumors. To do transfer learning on our dataset, they first normalized it before feeding it to the ResNet101 pretrained model. The ResNet101 model for classifying brain tumors is fine-tuned using this method. PCA is applied to this fused vector to generate the ultimate optimal feature vector. Many classifiers utilise This optimised feature vector as input to categorize tumors. Throughout the process, performance is evaluated. According to performance statistics, the proposed strategy increased prediction time on the medium neural network by 25.5x while maintaining 94.4% accuracy. Table 3 summarizes a careful analysis of previous studies' algorithms with characteristics and drawbacks.

One focus involved using deep learning algorithms to classify and detect MRIs, while another emphasized their use in preprocessing these images. Figure 8 illustrates the evolution of deep learning algorithm utilization between 2019 and 2022. However, there was tepid interest among individuals toward adopting deep learning. Notably, significant algorithm development occurred from around mid-2019 to 2022, during which experimentation with these algorithms was prevalent. By 2019, researchers began concentrating on enhancing MRI preprocessing, leading to the development of new deep learning algorithms tailored for this purpose. This shift also prompted a change in data augmentation techniques, moving from traditional methods to automatic approaches.

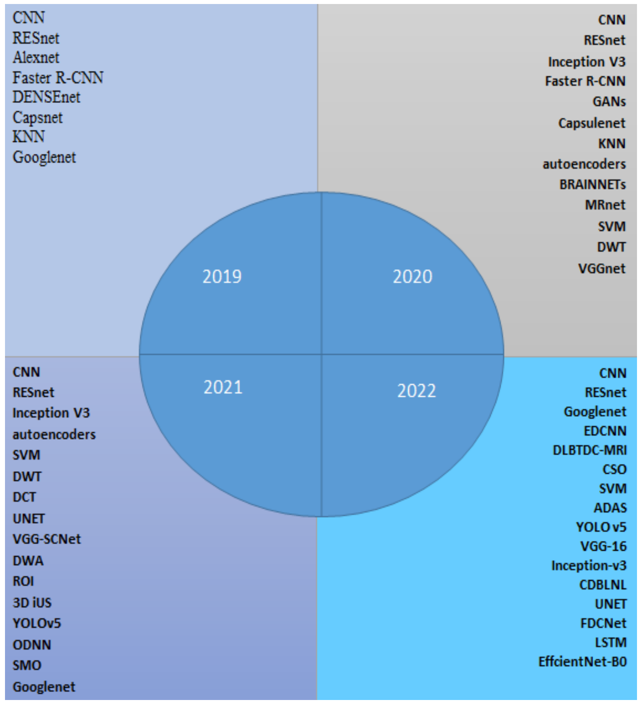

FIGURE 8. **Algorithmic development from 2019-2022.**

X. DISCUSSION

The discussion and findings of the research project on using Deep Learning algorithms for brain tumor identification and classification using MRI scans have illuminated several crucial aspects. Firstly, the analysis of the reviewed research papers revealed a substantial increase in the adoption of Deep Learning techniques for brain tumor analysis, signifying the growing acknowledgment of its effectiveness in this domain. The application of Deep Learning models has demonstrated remarkable outcomes in accurately detecting and classifying brain tumors, underscoring the prowess of these algorithms in managing complex and diverse imaging data. The comparative analysis of various Deep Learning methodologies has brought to light the strengths and weaknesses of different approaches. Convolutional Neural Networks (CNNs), recurrent neural networks (RNNs), and hybrid models emerged as frequently employed architectures. CNNs, with their capacity to autonomously learn hierarchical features, exhibited particular efficacy in extracting pertinent features from MRIs. However, the interpretability of some models remained a challenge, as deep neural networks often operate as enigmatic "black boxes," hindering an understanding of the decision-making process. Performance metrics played a pivotal role in assessing the effectiveness of the Deep Learning models. Accuracy, sensitivity, specificity, and the area under the receiver operating characteristic curve (AUC-ROC) were among the commonly used metrics. The substantial values achieved for these metrics attested to the robustness and accuracy of the models in discriminating between tumor and non-tumor regions. The discussion also highlighted the significance of high-quality MRI datasets for training and evaluating Deep Learning models. The availability of diverse and well-annotated datasets, encompassing various tumor types and grades, proved indispensable for ensuring

TABLE 3. A meticulous analysis of previous studies algorithms.

Authors	Datasets	Techniques	Characteristics(Drawbacks)	Accuracy
El Boustani et al. [44]	TCIA, Kaggle (tumour and non-tumour).	PNN is used for Seg, while CNN is used for classification.	There are no comparisons to cutting-edge techniques. Working with 3D MRI is not possible.	90%
Liu,D,& Dong,L.[45]	Cheng's Figshare (3064 images)	Average Pooling Residual Network on a Global Scale (G-RESnet)	Architecture that is deep and complex There is no training and assessment timetable, and no information on any pre-processing. The arrangement isn't suitable for 3D MRI volumes.	95%
Amin et al. [46]	ISLES strokes dataset from Miccai BRATS (2013-2017).	For seg, a criterion is set. Feature fusion is a collaboration between Alex and Google	Fusion of features has a complex architecture. As a result, mistakes might mount. The distinction in accuracy between employing match score fusion techniques with Google Net and Alexnet is rather negligible.	99%
Poonguzhali et al. [47]	It was not mentioned that the data of 20 patients was used for training.	SVM and Faster R-CNN	There is no information about the dataset or its annotations. There is no defined process. There were no parallels drawn. The amount of data available for training was relatively limited.	95%
Li et al.[48]	There are 3064 images from normal, meningiomas, and gliomas in the figshare collection plus 422 images from private datasets.	DENSEnet –LSTM DENSEnet-RNN, DENSEnet-DENSEnet	Auto-encoder datasets, such as dense-net (feature extraction), take an inordinate amount of time.	92%
Zhou & Li.[49]	The figshare dataset (3064 images)	CNN	The model can be compared to more up-to-date versions. CNN's results are quite brief, and there is little creativity.	87 %, 91 % and 92 %
Hossain & Shishir.[50]	The figshare dataset (3064 images)	Capsnet (CNN)	There is no standardized boundary extraction methodology. Only a few comparisons and outcomes have been made. There will be no pre-processing.	94.39%
Cheng, Yiming et al.[51]	Figshare, curated by Cheng, encompasses a comprehensive collection of (3,064 images).	CNN Concaps	Complicated construction with an abundance of parameters There are no comparisons with other algorithms.	93.5%
Siar and Teshnehlab [52]	BRATS (2016)	MUNIT-SIMGANs are used for refinement, PG-GANs for data augmentation, and RESnet-50 for detection.	The methodology employed is characterized by its profound complexity and demands a substantial investment of time and effort. It is worth noting that there is a conspicuous absence of literature reviews within this context.	96%
Ucuzal et al [53]	Figshare dataset (3064 images)	Capsnet (dilated capsule net)	Capsnet has no significant model distinctiveness. There isn't enough confusion in matrix comparisons and experiments.	95%
Adu et al.[54]	private dataset with 153 patients and 1892 images	(SoftMax, RBF, and DT) Alexnet (CNN)	There is no defined process and no comparisons with cutting-edge techniques. There is no information about pre-processing.	95%
Joshi et al [55]	Figshare dataset (3064 images)	CNN (auto-keras)	There have been no comparisons with cutting-edge models, and no confusion matrices have been created.	96%
Han et al. [56]	Miccai BRATS (2018)	3D-Multi CNNs	Inadequate review of the literature There were insufficient and novel experimental results. There isn't a big enough difference between single and multimodal.	96%
ezhilarasi and Varalakshmi [57]	BRATS 2015 and images from Radiopedia	CNN	There is no clear information on the modalities used (dataset). There is no obvious process. There are no parallels to cutting-edge models. Results have not improved significantly.	97%
Afshar et al.[58]	Public dataset (no info)	Alexnet	There are no comparisons to cutting-edge models. There is no testing performance. No performance metrics are included or discussed.	88%
Muthu Krishnammal and Selvakumar Raja	BRATS (2015)	Alexnet, VGG-16	All four strategies have the potential to generate better results. Other than normalization, there is no information on enhancement.	98%

TABLE 3. ***(Continued.)*** **A meticulous analysis of previous studies algorithms.**

[59]				
Deepak and Ameer [10]	Two different data sets (3064 and 516 images) (Figshare by Cheng and REMBRANDT)	One CNN for tumor classification and one CNN for tumor grading	16-layer complex architecture The rate of learning is rapid.	98%
Ali et al.[60]	figshare Dataset (3064 images)	Googlenet has been pre-trained (through transfer learning). SVM and KNN	Training duration is still long (55 minutes for optimal results).	96% 98%
Abiwinanda et al.[9]	50 brain MRIs	Alexnet, in conjunction with RPN, is used for classification using faster RCNN.	There has been no comparison with cutting-edge techniques. Results are limited. A scant review of the literature Information from an incomplete data set The dataset was pre-processed using software.	98%
Sultan et al.[61]	figshare Dataset (3064 images)	Transfer learning is used by Alexnet, Googlenet, and VGGnet (classification with SoftMax or SVM).	Complexity of preprocessing Time-complexity	98%
Kalaiselvi et al.[32] 202020	BRATS Whole Brain Atlas (WBA) 2013 (8 volumes).	6 CNN models	No information regarding data preprocessing The time is complexity The model is complex	96%
Maharjan et al.[62]	Figshare dataset (3064 images)	ELM-LRF CNN enhanced SoftMax and los functions	There has been relatively little gain in accuracy and processing time. There are no parallels to cutting-edge models.	97%
Kurup & Sowmya [33]	The figshare database (3064 images from 233 patients)	Capsule net	Training time isn't given, and the architecture isn't very deep	92%
To˘gaçar et al.[34]	Kaggle (Chakraborty created the dataset)	Within the realm of brain imaging, an MRNET is distinguished by its integration of advanced features, including CBAM, residual blocks, and the hyper column technique.	Architecture Is Complicated	96%.05
Bhanothu et al.[26]	Figshare by Cheng	VGG-16 is used as the base network in the F-RCNN and region proposals.	The duration of the testing is not depicted. The network of region proposal proposals is complex.	77%
Islam et al. [30]	Harvard Medical School (128 images of brain tumors)	Thresholding and watershed are used to segment the data, and then SVM is used to classify it	There is no information about the CNN architecture that was employed. There is no information on the length of training testing or the complexity of earlier segmentation.	78.4%
Sharif & Li.[37]	BRATS 718, 141,13,	Inception V3 pre-trained CNN	In terms of FE and concatenation, the model is complex and time-consuming. Due to feature fusion, the computing time has increased.	92%
Han et al.[41]	BRATS 2016	Resnet-50 for detection and PG-GANs for DA	With the most up-to-date method, more comparisons may be done. There is no information on the length of training and examination. There are no graphs that indicate convergence.	91%
Raja and Viswasa [23]	BRATS 2015	JOA (java optimization algorithm) based on deep autoencoders and SoftMax regression	The difficulty of extracting features	98.5%
Çinar and Yildirim [28]	Kaggle dataset for brain tumor detection	Resnt50 as baseline network	Because of the additional 8 levels, the architecture has become more complex. There is no novel approach.	97%
Abdelaziz Ismael et al.[64]	Figshare (3064 images)	MRI scans is utilized as input for training and testing the Resnet50 architecture.	There is nothing new here. The architecture is the same. As a result of augmentation, the parameters have been increased.	98%
Amin et al.[25]	BRATS dataset 2012, 2013, 2014, and 2015	Used (SSAE) for Stacked Sparse Autoencoder.	SSAE's shallow architecture There was little improvement in accuracy or computational time.	98%
Amin et al. [35]	BRATS 2012 2013, 2015, 2018	For feature fusion, use DWT. CNN is used for classification.	Complex approach due to an increase in the number of parameters as a result of fusion Especially good for merged images.	
Ozyurt et al. [29]	cancer genomic atlas for glioblastoma multiforme (TCGA-	ELM and SR-FCM- (CNN) segmentation and feature extraction were used.	The procedure is complicated and time-consuming. There will be no comparisons to cutting-edge technology.	98%

TABLE 3. *(Continued.)* **A meticulous analysis of previous studies algorithms.**

	GBM) and cancer imaging archive (TCIA) database (500 samples)			
Anilkumar and Rajesh Kumar [36]	BRATS and CE-MRI	VGGnet and KNN as classifiers, block-wise fine tuning and transfer learning.	The architecture in question appears to exhibit a high level of intricacy, yet it lacks crucial details regarding the training and testing phases. Furthermore, the absence of convergence graphs to visualize the model's performance trends further limits the comprehensive assessment of its effectiveness.	97.28% 98.69
Megha [65]	Kaggle	CNN	The provided information regarding the CNN architecture lacks technical specifics, leaving critical details unanswered. Similarly, there is a dearth of information regarding the pre-processing methods employed. Furthermore, details about the duration of both training and testing phases remain undisclosed. Additionally, the absence of algorithm convergence graphs hinders the ability to gauge the model's learning dynamics and convergence patterns.	90-99%
Sarhan [66]	Cheng's figshare (only 170 for each class)	deep learning CNN (5 layers)	This study lacks comprehensive comparisons with state-of-the-art methodologies, as it primarily focuses on evaluating the SVM approach. Moreover, the employed simple CNN model appears to lack significant originality or distinctive innovations in its design or approach.	98.5% For SVN, 99.3% for CNN
Begum and Lakshmi [40]	dataset (1000 images)	RNN	There is no information available regarding the imaging modalities considered (2D or 3D). Because of the FE headache, things are complicated and exhausting.	96%
Raj et al.[67]	Figshare (613 for classification and 4689 for detection), BITE, OASIS (pre-post tumor dataset), and OASIS (pre-post tumor dataset).	2 BRAINNETs for Classification and detect	There is no information on the length of testing and training, nor on the sophisticated 22-layer design.	98% For detection, 99% For classification
El boustani et al.[68]	Kaggle, TCIA	CNN	There are no comparisons with cutting-edge methods. Cannot be used with 3D MRI.	98%
A. Deshpande et al.[69] 20212021	RIDER-NEURO-MRI 2015 Data	DCT-CNN-ResNet50	The DCT-CNN-ResNet50 was tested on one dataset. Additionally, their fusion method works well only with ResNet50 while failing with other pre-trained networks.	98.14%
T. Sadad et al.[70]	Figshare dataset (Brain tumor)	using Unet with ResNet50	One potential drawback of using a combination of UNet and ResNet50 is the increased complexity of the model, which may lead to longer training times and higher computational requirements.	95%
A. Rehman et al.[71]	BraTS datasets 2015,2017, and 2018	create a 3D convolutional neural network (CNN)	Training 3D CNNs can take a significant amount of time, which can be a drawback when working with large datasets.	98.32, 96.97, and 92.67%,
Latif et al.[72]	BraTS 2015, 2017 and 2019	UNET	Because MRI works on 2D slices by slice, they assume they can ignore the depth information. Seeing how this architecture is expanded to 3D volumes will be fascinating.	91%
Majib et al.[73]	collected from Pathology Institute in(Bangladesh)	used VGG-SCNet, to classify brain cancers from MRI	First, the number of images analyzed in this study is limited, whereas including additional images may strengthen the study. Second, no conventional image processing-based categorization techniques were examined.	%99.2
El Kader et al.[74]	BRATS (2012, 2013, 2014, 2015) and ISLES-SISS 2015	used (CNN-DWA)	Its disadvantages are that they are too sluggish for huge data sets and that the approaches are similar to the uncertainty of complex CNN parameters.	98%
Shafi et al.[75]	collected of the Nanfang Hospital,	Region of interest (ROI),dSVM classifier.	The scarcity of early-stage tumor and lesion data necessitated the use of datasets primarily comprising	98%

TABLE 3. *(Continued.)* **A meticulous analysis of previous studies algorithms.**

	Guangzhou, China, 2015		intermediate-stage cases.	
Rai et al. [76]	TCGA (The Cancer Genome Atlas) medical imaging data.	model UnetResNext-50 and Vanilla Unet	The prediction was made with the help of reserved test images that had not been exposed throughout the training operation. vanilla UNet may struggle to capture more complex and high-level features in the image due to its shallow architecture, resulting in lower performance on certain tasks.	95.73%
Angel-Raya et al.[77]	Collected from the Leipzig University Hospital.	Using pMRI and 3D iUS data	create a brain tumor model that can be used for operation planning is one of these methods.	86.79%
R. Singh et al.[78]	BRaTS dataset	Gabor-modulated convolutional filter.	Not capture all of the relevant features that distinguish different types of tumors. Additionally, the filter may be sensitive to noise and other image artifacts, which could result in misclassification of tumors. Finally, the computational complexity of the filter may be high.	98.68%
Rai and Chatterjee et al.[79]	MR Dataset	(LeUNet)	(LeU-Net) has not been evaluated on a large number of datasets.	94%
Anantharajan and S. Gunasekaran [80]		autoencoder (DAE) along with (BMOA) and random forest (RF) classifier	Computational Complexity: Deep autoencoders are computationally intensive and require significant computational resources to train and evaluate.	95.84%
Sugimori et al.[81]	Hokkaido University Hospital	ResNet CNN architecture	A less number of images were used via brain MRI classifications that may cause overfitting during training process	99%
M. C. Xenya et al.[82]	tumor-classification dataset(2021)	incorporating 3 base learners (VGG16, Inception-V3, ResNet50)	The base learners incorporated, the more complex the model becomes, making it more difficult to interpret and debug.	98.11%
N. M. Dipu et al.[83]	BRATS 2018 dataset	Detection and classification using YOLOv5 and FastAi.	One major drawback of YOLOv5 and FastAI is that they require large amounts of labeled data to train accurately. Without enough labeled data, the models may not be able to accurately detect and classify objects.	85.95% and of 95.78%
Abd El Kader et al. [84]	BRATS2012, BRATS2013, BRATS2014, BRATS2015	DWAE model	needs to be trained for an extended period of time	99.%
Preethi and P. Aishwarya [85]	collected from MRI and CT [internet, Brain Imaging Resources]	(DWT), (ODNN). (SMO) algorithm.	The usage of a DNN and SMO algorithm implies that the approach may necessitate large processing resources, which may restrict its practical usefulness in some instances.	94%
Deb and S. Roy et al. [86]	BRATS (2012, 2015 and 2016)	frog leap enhancement deep fuzzy adaptive neural network	Did not work on lower the classifier's computational time. Because reducing the computational burden of learning allows for more processing time. To evaluate performance, Multiple data sets were not compared.	99.6%
Bagyara et al.[87]	database'SITBMRI'(500 images)	5U-Net and U-Net with DenseNet	The limited data for potential generalization challenges, unclear methodology description, potential experimental design gaps, inadequate data preprocessing details, and complex model requirements.	88.7%
Kumar, J. Kakarla et al. [88]	brain tumor dataset (Cheng)	ResNet-50 and global average pooling were employed.	If the input images are too small, the network may not be able to learn enough features to make accurate predictions.	97%
Suraj Patil et al. [89] 20222022	Kaggle brain tumor (3064 images)	a novel new ensemble (EDCNN)	The model could overfat to the training data, which would make it less accurate on new, unseen data. This could be particularly problematic if the training data is limited or not representative of the broader population of brain tumor patients.	97.77%
P. Mohan et al. [90]	BRATS 2015	combining DLBTDC-MRI and CSO	Combining the two approaches can make interpreting and validating the results difficult.	96%
S. Maqsood, et al. [91]	BRATS 2018 and Figshare datasets	M-SVM is then used, followed by a modified MobileNetV2 and a custom 17-layered deep neural network design.	Diminished image contrast, erroneous delineation of tumor regions stemming from artifacts, the computational intricacy associated with methodologies demanding additional time for precise tumor	98%

TABLE 3. ***(Continued.)*** **A meticulous analysis of previous studies algorithms.**

			localization, and the inherent need for a significant volume of training data to surmount the predicament of overfitting within prevailing deep learning techniques.	
Mehnatkesh et al.[92]	Kaggle brain tumor MRI (3064)	IACO-ResNet	One of the key flaws of the proposed strategy is its time-consuming nature.	99%
Chattopadhyay et al.[93]	BraTS 2020 (total of 2892 images)	SVM classifiers and additional activation approaches (softmax, RMSProp, sigmoid, and so on)	Training an SVM classifier can be time-consuming and requires a significant amount of computational resources.	99.74%
Tiwari et al.[94]	Kaggle licensed CCO: Public Domain	CNN is utilised to classification the brain image into four categories	CNNs normally require huge amounts of data to train efficiently, and if the four categories of brain images have a limited amount of data available, the CNN may be unable to learn the essential patterns to categorize the images accurately.	99%
Han-Trong et al.[95]	data collected from Bach Mai Hospital Vietnam	uses ADAS optimization and AI algorithms	The system also has the problem of still having a tiny dataset. In the future, in addition to collecting more data to improve the system's accuracy.	94%
Shelatkar et al.[96]	Brats 2021	YOLO v5. From the RSNA-MICCAI brain tumor classification.	One drawback of YOLO is that it may not be as accurate as other object detection techniques such as Faster R-CNN or Mask R-CNN, especially when it comes to detecting smaller objects. YOLO also struggles with detecting objects that are partially obscured or have complex shapes.	88%
Amin et al. [97]	Kaggle 2020-BRATS	Quantum Variational Classifier	When extracting features from a pre-trained model like InceptionV3, some information may be lost in the process. The deeper the layer from which the features are extracted, the more abstract and less specific the information becomes. This could potentially limit the performance of the QVC, as it may not have access to all the relevant information needed to make accurate predictions.	90%
Srinivas et al.[98]	Collection from the Kaggle dataset	Inception-v3 models and ResNet-50, VGG-16, to autonomous prediction are compared.	The ResNet50 model's performance results are expressed in a confusion matrix, with the model predicting malignancies from testing data and classifying 11 MRI brain images out of 31 as false negatives, which is the model's disadvantage.	78% and 86%
Saravanan,Kumar et al.[99]	BRATS and REMBRANDT	The CDBLNL method for classifying with CNN layer.	To train, CDBLNL necessitates a significant amount of processing power and memory, particularly for large datasets or complicated topologies.	97.2%
Pedada et al.[100]	BraTS 2017, 2018	U-Net structure modification	Modifying the structure of the U-Net may result in reduced accuracy, speed, or both performance.	93.40% and 92.20%
Raza et al.[101]	Tianjin Medical University General Hospital and Nanfang Hospital, in Guangzhou China from 2005 to 2010, CE MRI .	The CNN model's GoogLeNet architecture	With its many layers and complex architecture, it can be difficult to interpret how GoogLeNet makes its predictions. This can make it challenging to debug and improve the model.	99%
Molaei, Ghorbani,et al.[102]	BraTS	FDCNet is a deep neural network using fuzzy convolution.	The study produced a number of minor inaccuracies, which are visible in the line of best fit. Some errors occurred when the data was not within the range of measurement in certain areas.	98.68%
Sangeetha, Muthukumaran et al.[103]	REMBRANDT	MCTL used to categories 3D MRIs	MCTL can be computationally intensive, especially for large datasets, which may limit its practicality for some applications.	94%
Demir, Akbulut et al.[104]	BRATS 2015 and 2018	In the architecture of the 3ACL models, intricate designs featuring attention, convolutional, and LSTM structures were seamlessly integrated within a unified learning framework.	The 3ACL model requires a considerable amount of time to train, especially when dealing with large datasets. This can be a significant obstacle, especially when developing models for time-critical applications.	98.90% and 99.29%

TABLE 3. ***(Continued.)*** **A meticulous analysis of previous studies algorithms.**

Shah, Saeed et al.[105]	Image Net dataset	adjusted the EffcientNet-B0 base mode	It may require more memory and computational resources than smaller networks, making it difficult to use on low-end devices.	98.87%
Salama and Shokry.[106]	brain tumor MRIs	based on variational convolutional generative models	A model trained on a particular dataset may not perform as well on fresh or previously unseen data. It must be validated across multiple datasets to determine the model's generalizability.	96.88%
Anaya and Mera [107]	dataset MRI	ResNet50	the use of a complex ResNet50 model that may struggle with a small dataset, potential issues with gradient fading, and noise introduction via PCA-based augmentation. Transfer learning's effectiveness varies with data similarity, and the choice of the loss function is not discussed.	92.34%
Zahid et al.[108]	BraTS2018	use of the FLAIR, T1, T2, and T1CE	Each sequence takes a certain amount of time to acquire, which can increase the total time required for the MRI scan.	94.4%

the models' generalizability. Commonly employed data augmentation techniques, such as image rotation, flipping, and scaling, were instrumental in enhancing the model's ability to cope with different scenarios. While the findings underscored the tremendous potential of Deep Learning in the field of brain tumor analysis, several limitations were identified. Challenges included the demand for extensive computational resources, the need for substantial amounts of annotated data, and the risk of overfitting. Additionally, the lack of interpretability in some models raised concerns about the transparency and reliability of the predictions. For future work firstly, the interpretability and explainability to Addressing the challenge of model interpretability is paramount. Future research should explore techniques to make Deep Learning models more transparent and interpretable. This will enhance their adoption in clinical practice and foster trust among medical professionals. Secondly, Data Quality and Diversity need to creation of more diverse and comprehensive datasets is essential. Future efforts should focus on curating datasets that encompass a broader spectrum of tumor types, stages, and patient demographics to improve the generalizability of Deep Learning models. Thirdly resource-efficient models make Deep Learning more accessible; research should concentrate on developing resource-efficient models that deliver accurate results with reduced computational requirements. This will enable healthcare institutions with limited resources to leverage these technologies. Fourthly, transfer learning exploring and adapting pre-trained models from other domains for brain tumor analysis holds promise. This approach can reduce the need for extensive labeled data and expedite model development. Lastly, the findings of this study underscore the potential and promise of Deep Learning in revolutionizing the diagnosis and prognosis of brain tumors, ultimately leading to improved patient care and outcomes. However, it is crucial to address the identified research gaps and explore these future avenues for enhancing the interpretability, generalizability, and transparency of Deep Learning models to fully unlock their benefits in clinical practice. By overcoming these challenges, Deep Learning can contribute significantly to advancing the field of brain tumor analysis and ultimately improve patient outcomes. The findings from this research will provide researchers with a comprehensive understanding of the current landscape of deep learning methodologies for brain tumor identification and classification, facilitating further advancements in this critical field of medical research.

XI. CONCLUSION

In conclusion, this review paper has systematically examined the utilization of Deep Learning algorithms for the identification and classification of brain tumors in MRI scans, spanning the period from 2019 to 2022. The comprehensive analysis and comparison of various Deep Learning methodologies have yielded valuable insights into the current landscape of research in this domain. The evaluation of performance metrics has unequivocally demonstrated the efficacy of these algorithms in accurately detecting and categorizing brain tumors. The methodology employed in this research project involved a meticulous review of relevant literature, encompassing the identification of research publications through a systematic approach. These publications underwent a detailed analysis, encompassing the evaluation of deep learning methodologies, comparison of performance metrics, and scrutiny of associated advantages and disadvantages. The outcomes derived from this methodological approach aspire to furnish researchers with crucial insights, empowering them to navigate the diverse landscape of Deep Learning approaches for brain tumor identification and classification. An upcoming project aims to leverage pre-trained models from diverse fields to analyze brain tumors. This innovative strategy minimizes the necessity for vast labeled datasets and accelerates the pace of model creation. The overarching goal of this review is to contribute to the advancement of medical research in the critical area of brain tumor identification. By continuously refining and optimizing Deep Learning algorithms, researchers can unlock the full potential of this technology, thereby furthering our comprehension of brain tumors. Ultimately, these advancements hold the promise of enhancing patient outcomes through more accurate and timely tumor detection. The ongoing pursuit of excellence in Deep Learning methodologies will undoubtedly play a pivotal role in shaping the future of medical diagnostics and treatment strategies for individuals afflicted by brain tumors.

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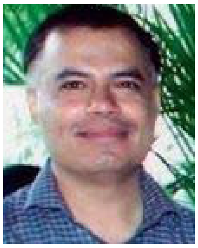

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