Brain Tumor Classification using Deep Learning: A State-of-the-Art Review

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ABSTRACT

Given that the number of available brain tumor images has grown, Deep Learning (DL) plays a critical role in brain tumor classification in terms of accurately diagnosing and predicting such tumors. Regarding the classification of several large-scale images, DL-driven techniques, such as convolutional neural networks, have not only shown significant results, but have also demonstrated that they can progressively learn features from data at multiple levels. As the use of medical imaging for analysis and education grows in popularity and the same occurs with the unstructured multi-faceted nature of the data, a state-of-the-art review of brain tumor classification is important. This study provides a systematic review of the state-of-the-art techniques and approaches utilized to classify massive Magnetic Resonance Imaging (MRI) data, especially for cancerous brain tissues. Thorough research was conducted on the subject of DL utilization in brain tumor classification based on studies between 2020 and 2023 derived from a variety of scholarly databases. Of the 142 studies retrieved, 20 were included to investigate the proposed or applied DL techniques for the recognition and categorization of brain tumors using MRI. A meta-analysis of current DL classification techniques, algorithms, and their validation was introduced. Overall, DL techniques should receive more attention due to their automatic and accurate feature extraction capacity.

Keywords-deep learning; brain tumor; machine learning

I. INTRODUCTION

DL is a type of Machine Learning (ML) that excels at handling unstructured data. The DL processing concept has been considered as the gold standard in ML because it outperforms traditional ML methods. Furthermore, it has gradually become the most widely used computational approach in ML, achieving outstanding outcomes in a range of complex intellectual tasks that are met on even better social behaviors. One of the benefits of DL is its capability to understand huge volumes of data.

Recently, DL has grown rapidly, and it has been extensively used to positively address a large variety of traditional uses in many domains, especially in medical images. Recent advances in ML, especially with regard to DL, are helping to identify, classify, and quantify patterns in medical images. At the basis of these advancements is the capacity to use the hierarchical feature representations learned simply from data rather than from features created by hand based on domain-specific knowledge.

When working with unorganized data, DL achieves more power and elasticity due to its capability to deal with various elements. A DL algorithm iteratively processes data over several levels, with its every level being capable of obtaining elements and shifting them to the next level. The first levels acquire low-level elements and the subsequent levels combine them to form a full description.

Therefore, in the last few years, ML algorithms have been utilized to teach a workstation system to become an "expert system." One such utilization is in the health domain, where health imaging is used for analysis and education [1, 2]. Here, DL algorithms use Artificial Neural Networks (ANNs) that progressively learn with a large approximation to the human brain in order to accurately solve a given problem [3]. Researchers and scientists have proposed various methods, approaches, techniques, and tools to classify normal (i.e., not tumor) or abnormal (i.e., tumor) brain skins and detect brain tumors in the initial phases to enhance the treatment procedure and regulate the array of malignant matters.

This study aimed to carry out a Systematic Review (SR) and provide an overview of the existing scholarly methods, tools, techniques, and approaches that were proposed or developed to classify MRI brain images according to the presence of tumors and to detect brain tumors in the early stages. The main key stages of conducting an SR are being formulated by Research Questions (RQ), determining the inclusion and exclusion criteria, and identifying the source materials (electronic databases) before providing the results and a summarization. This study addresses three main RQs:

- RQ1: What are the main features of brain tumor diagnosis?
- RQ2: What are the existing methods, techniques, and approaches used to classify brain tissue and detect brain tumors?
- RQ3: What are the challenges in classification techniques that are faster and more accurate than traditional methods?

To answer the RQs of this SR, the following inclusion criteria were determined:

- Research papers and articles from the IEEE Xplore Digital Library, MDPI Digital Library, Web of Science, Springer database, Google Scholar, and ScienceDirect electronic online databases.
- Research papers and articles compiled in English.
- Papers published in the last four years (2020–2024).
- Papers and articles related to web videos and YouTube videos from a cyber-security perspective.
- Papers from conferences and articles published in indexed databases.
- Articles and papers that used standard MRI datasets.

The exclusion criteria were:

- Books.
- Theses.
- Notes.

The steps for the searching method based on research questions, such as what key word of research is, which indexed database of publication and how many articles were found, are all shown in Figure 1. Table I portrays how many articles were found and selected of each Digital Library of indexed database.

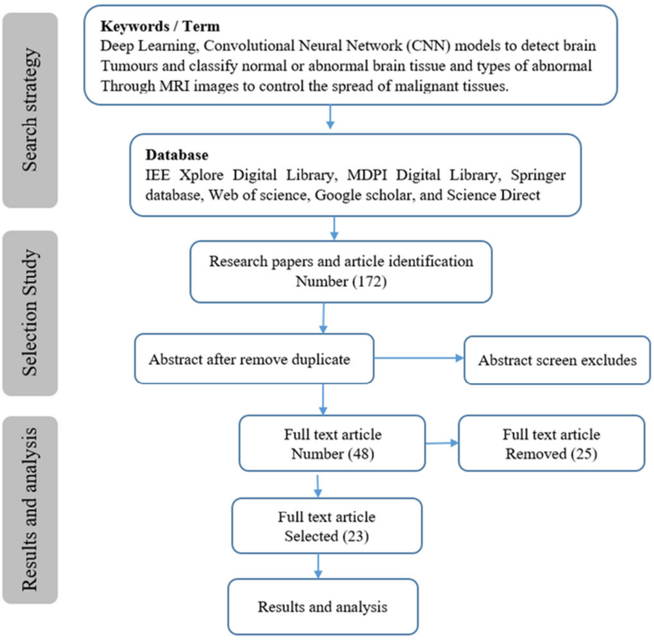

Fig. 1. The method of searching articles and papers based on research questions.

TABLE I. THE AMOUNT OF ARTICLES WHICH WERE FOUND AND SELECTED FROM EACH DIGITAL LIBRARY

Databases	Found	Selected
Google Scholar	33	6
IEEE Xplore	24	3
MDPI	41	7
Springer	27	3
ScienceDirect	18	4

II. THE BACKGROUND

The DL approach is essential to primary research areas about creating intelligent machines. This approach has had a major effect on various fields, such as image processing, tumor analysis, accuracy, medicine, self-driving vehicles, analytical forecasting, speaking identification, and Natural Language Processing (NLP) [3-8]. The ANNs were based on the biological nervous system of humans and especially the NN form was based on the majority of the earliest perceptions of the human brain system [9-10]. Authors in [11] describe the architectures of ANN.

A Convolutional Neural Network (CNN) is a type of a Deep Neural Network (DNN), and is the most popular DL model [12, 13]. It derives its name from the logical linear operation of convolution between matrices, and it has a deep, feed-forward architecture with an incredible generalization potential compared with other networks [14]. The structure of CNNs in DL is presented in Figure 2.

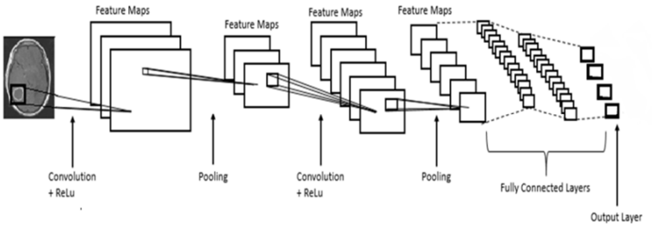

Fig. 2. The structure of CNNs in DL.

CNN architectures are a special version of the ANN design that involves feature mining and generally comprises of a mixture of linear and nonlinear processes, such as complexity and stimulation functions. The CNN network topology is constructed around three core ideas: local open areas, mutual weights, and spatial or temporal testing [10, 15]. The fundamental building blocks of CNN architectures are input layers, hidden layers which include convolutional layers [16-18], pooling, completely connected layers, and output layers. There are various options to process convolutional layers, but at the same time, these options are reduced by certain side effects, such as stride and padding [16, 19]. However, after the convolutional layer has completed its mission, it will be transported to the next layer in the CNN, which is the non-linearity layer. By passing the induced output of the convolution layer through a non-linear activation function, non-linearity can be used to modify or cut off the output [16]. The main task of the activation function in a non-linear model is to map the input into the output, calculate the weighted number of the input of the neuron, and decide whether a neuron can generate an appropriate output for a given input [17]. CNN is using three main functions:

- Rectified linear unit (ReLu) $f(x)=\max(0,x)$ as an activation function [15, 17, 19].
- Sigmoid function $\sigma(x)=\frac{1}{1+e^{-x}}$ [14, 18].
- $f(x)=\tanh x=\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$].

The structure of the activation function process in CNN using DL is [17]:

The pooling layer, also referred to as subsampling, is a common downsampling operation that reduces feature resolution [10, 15]. There are two approaches for pooling strategies that are deployed in various pooling layers: max pooling and average pooling [21-24]. Fully Connected Layers (FCLs) are the last layers in the CNN model. These consist of a generic multi-layer network, also known as dense layers. The CNN architecture employs the FCL as its output layer (classifier) [24]. The tasks of FCLs include taking the final convolution or pooling layer's output feature maps, transforming them into a one-dimensional array of numbers (or vectors), and connecting them to one or more completely connected layers.

III. DISCUSSION AND ANALYSIS

Table II presents the methodologies, techniques, and datasets that were utilized for the classification and identification of brain tumors in MRIs and Figure 3 shows the number of research papers by years.

TABLE II. RELEVANT RESEARCH DETAILS

Ref	Method	Number of Images	Classification	Accuracy (%)	Publication Year
[25]	CNN with two different convolutions block	3064 T1-weighted contrast-enhanced	Meningioma, glioma, and pituitary	97.39	2020
[26]	Multi-scale 3D CNN framework	The dataset comprises 284 subjects that, include 209 HG and 75 LG glioma tumors	HG and LG glioma tumors	96.49	2020
[27]	Hybrid CNN-NADE	3064 T1-weighted contrast-enhanced	Meningioma, glioma, and pituitary	95.05	2020
[28]	Multiscale CNN	3064 T1-weighted contrast-enhanced	Meningioma, glioma, and pituitary	97.3	2021
[29]	Fuzzy C-means and VGG16	577 T1-weighted	Normal images and tumor images	96.7	2021
[30]	MobileNetV2	2,513 brain tumor images and 2,087 healthy images	Tumor images and healthy images	92	2021
[31]	Hybridized CNN classified	577 T1-weighted	Normal images and tumor images	96.15	2020
[32]	Hybrid DeepTumorNet	3064 T1-weighted contrast-enhanced	Meningioma, glioma, and pituitary	99.67	2022
[33]	Differential deep-CNN mode	17,600 MR brain images, which includes T1, T2, and FLAIR images	Normal and abnormal MR brain images	99.25	2021
[34]	Inception-v3-Ensemble	3064 T1-weighted contrast-enhanced	Meningioma, glioma, and pituitary	94.34	2021
	Xception-Ensemble			93.79	
[35]	Developed transfer-learned CNN	3064 T1-weighted contrast-enhanced	Meningioma, glioma, and pituitary	95.75	2022
[36]	17-layered CNN, MobileNetV2 & M-SVM	3064 T1-weighted contrast-enhanced	Meningioma, glioma, and pituitary	98.92	2021
[37]	CNN Model	3000 MRI Brain images	Tumor images and healthy images	96.33	2022
[38]	Incecption-v3 CNN model	3064 T1-weighted contrast-enhanced	Meningioma, glioma, and pituitary	99.43	2020
	DensNet CNN model			99.51	

[39]	Hybrid method (Google-Net + SVM)	3064 T1-weighted contrast-enhanced	Meningioma, glioma, and pituitary	98.1	2022
	Hybrid method (Google-Net + Fine-Tuning)			93.1	
[40]	VGG-16	256 MRI images	Benign (noncancerous) and Malignant (cancerous)	96	2022
	Inception-v3			78	
	ResNet50			95	
[41]	Hybrid method (SqueezeNet + SVM)	3064 T1-weighted contrast-enhanced	Meningioma, glioma, pituitary and Not-Tumor	98.7	2023
[42]	Comparision seven deep (CNN)	7023 MRI images.	Meningioma, glioma, pituitary and healthy brains	97.12	2023
[43]	MCNN classification model	233 Images of Contrast-Enhanced T1-Weighted	Meningioma, glioma, and pituitary	99.89	2023
[44]	Novel 2D CNN Novel 2D CNN architecture and a convolutional auto-encoder network	3264 MRI image	Meningioma, glioma, pituitary and healthy brains	96.47	2023
[45]	Hybrid method (newly design nine-layered CNN model + (MC-SVM))	BRATS	Benign and Malignant	99.06	2024
[46]	ResNet50V2	7023 MRI images.	Meningioma, glioma, pituitary and Not-Tumor	96.34	2024
[47]	ResNet 12, DenseNet, YOLOv8, and MobileNet	4,489 images	14 types of brain cancer	97.3 YPLOv8	2024

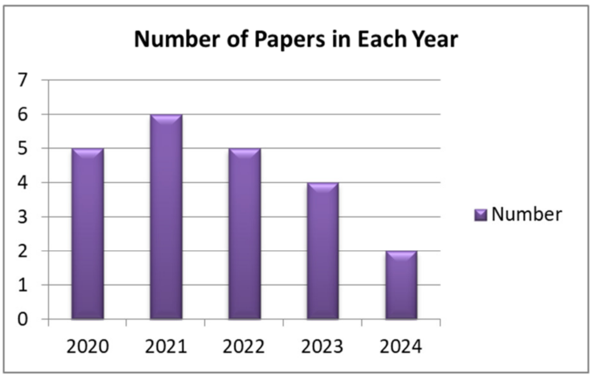

Fig. 3. The number of papers by year.

The research examined 23 investigative articles, in which most of the scholars employed private datasets (images collected using an MRI scan). Figure 4 presents each percentage.

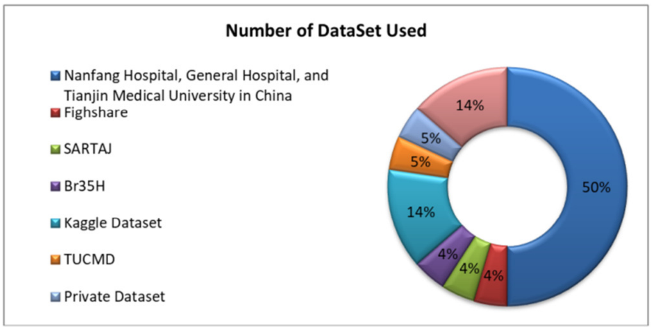

Fig. 4. The datasets used in the articles reviewed.

Regarding the classification of MRI brain types in the 23 research papers studied, the majority of tumors are classified as meningioma, glioma, and pituitary tumors (Figure 5).

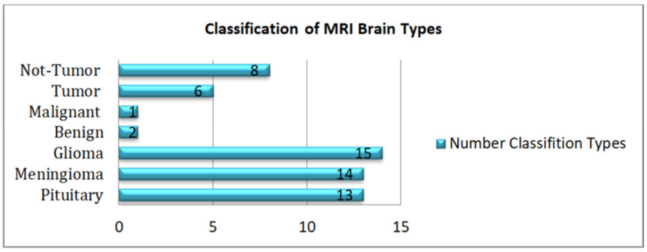

Fig. 5. The classification of MRI brain types.

As for the number of metrics which had been used in DL algorithms in the various papers published in recent years (2020 – 2024), most of them employed accuracy and precision, while less of them employed F1-score and recall (Figure 6).

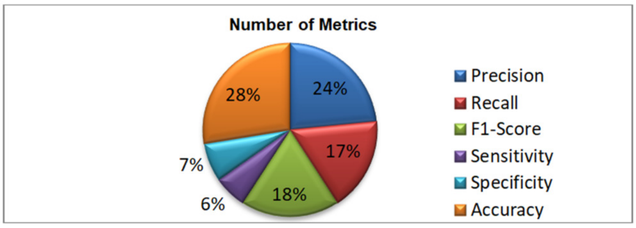

Fig. 6. The number of metrics used in DL algorithms.

Table III presents the standard metrics used in each research study and the percentage of each metric utilized with each method.

The performance of each method in the DL algorithms of the different papers published between 2020 and 2024 using precision, F1-Score, recall, specificity, and sensitivity measurements is detailed in Figure 7. The performance of the 23 research articles reviewed in terms of accuracy was evaluated, with the results presented in Figure 8.

TABLE III. METHODS AND METRICS

	Method(s)	**Precision (%)**	**Recall (%)**	**F1-Scor (%)**	**Sensitivity (%)**	**Specificity (%)**	**Accuracy (%)**
[25]	CNN with two different convolutions block.	95.44	96.94	96.11	-	-	97.39
[26]	multi-scale 3D CNN framework	-	-	-			96.49
[27]	Hybrid CNN-NADE	94.49	-	94.56	94.64	97.42	95.05
[28]	Multiscale CNN	-	-	-	94		97.3
[29]	Fuzzy C-means and VGG16	97.05	-	97.05	97.05	96.25	96.70
[30]	MobileNetV2	92.5	-	92			92
[31]	Hybridized CNN classified	96.11	-	96.53			96.15
[32]	Hybrid DeepTumorNet	99.6	100	99.66			99.67
[33]	(differential deep-CNN)	97.22	-	95.23	95.89	93.75	99.25
[34]	Inception-v3-Ensemble	93	92.33	92.66	-	-	94.34
	Xception-Ensemble	91.33	90.66	90	-	-	93.79
[35]	Developed transfer-learned CNN	-	-	-	-	-	95.75
[36]	17-layered CNN, MobileNetV2 & M-SVM	-	-	-	98.82	99.02	98.92
[37]	CNN Model	97.93	-	96.44	95	75.72	96.33
[38]	Incecption-v3 CNN model	99.3	99.5	99.25			99.43
	DensNet CNN model	99.3	99.42	99.35			99.51
[39]	Hybrid method (Google-Net + SVM)	98.37	98.17	-			98.1
	Hybrid method (Google-Net + Fine-Tuning)	92.12	94.32	-			93.1
[40]	VGG-16	94	100	98	-	-	96
	Inception-v3	75	70	73	-	-	78
	ResNet50	92	89	94	-	-	95
[41]	Hybrid method (SqueezeNet + SVM)	98.3	98.7	98.5			98.7
	Hybrid method (SqueezeNet + Fine-Tuning)	97	96.5	96.5			96.5
[42]	Comparison seven deep (CNN)	97.97	96.59	-	-	99.84	97.12
[43]	MCNN classification model	97.98	97.87	98.79	-	100	99.89
[44]	Novel 2D CNN architecture	94.75	95.75	-	-	-	96.47
	Convolutional auto-encoder	94.25	94.25	-	-	-	95.63
[45]	Hybrid method (newly design nine-layered CNN model + (MC-SVM))	-	-	-	-	-	99.06
[46]	ResNet50V2	96.41	96.11	96.10	96.11	97.41	96.34
[47]	ResNet 12, DenseNet, YOLOv8, and MobileNet	-	-	-	-	-	97.3

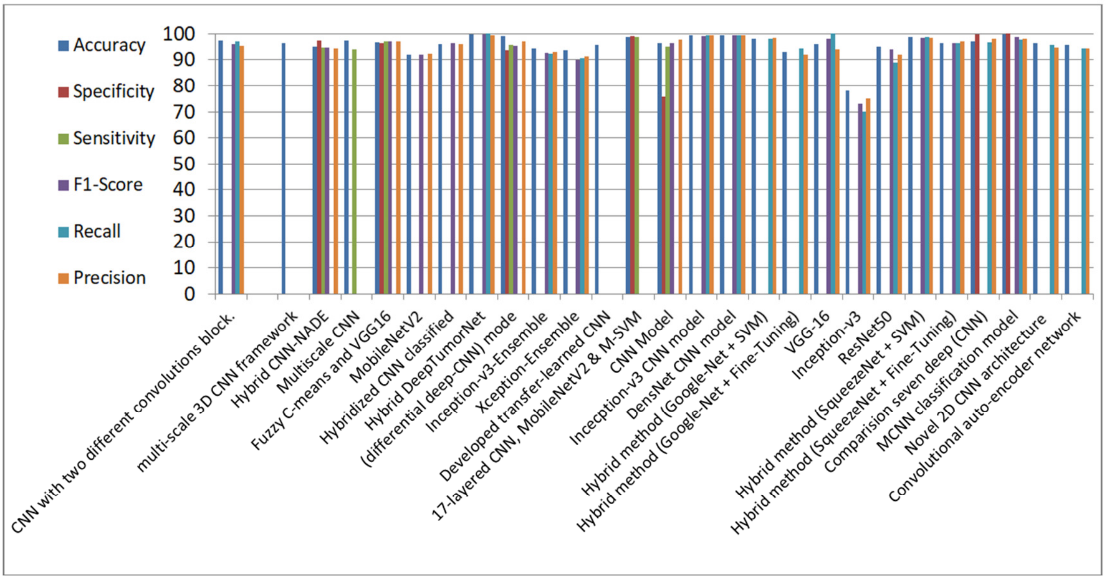

Fig. 7. The performance of each method using precision, F1-Score, recall, specificity, and sensitivity metrics.

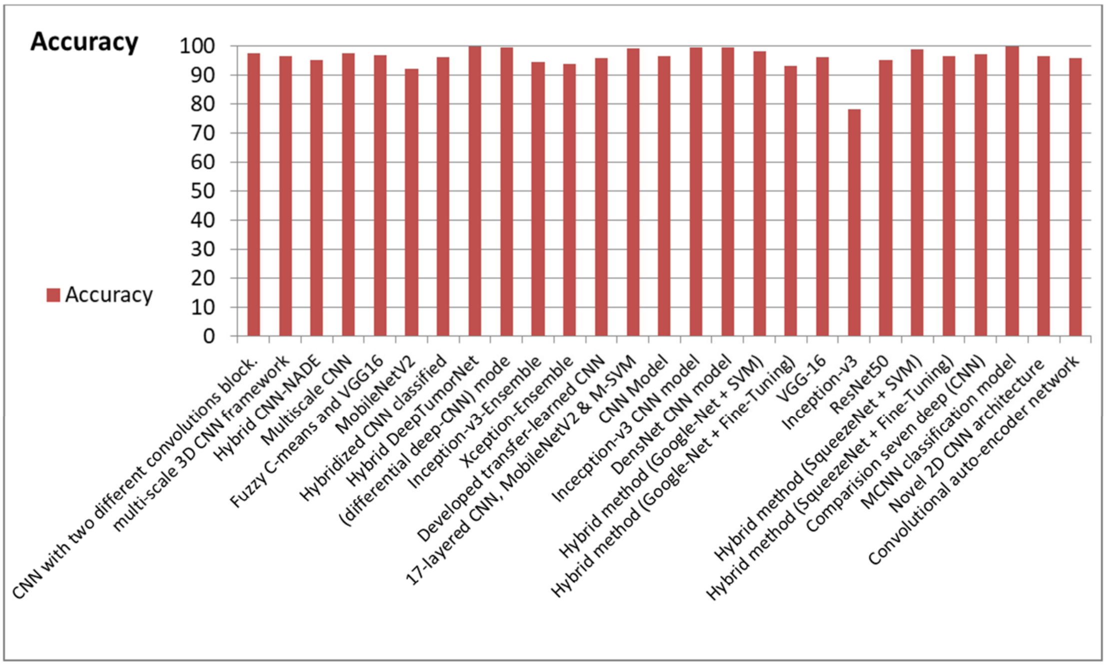

Fig. 8. The performance of each method in terms of accuracy.

Over the decades, the application of ML and DL approaches has facilitated the identification and categorization of brain tumors using various imaging modes, such as MRI [45, 48, 49]. In this study, 16 articles were examined to explore the DL methods followed to identify and categorize brain tumors in MRIs, emphasizing the difficulties associated with the DL algorithms reported in recent publications (2020 – 2024). This paper reviewed the fundamental techniques used by researchers in registering images, detecting anatomical and cellular structures, segmenting tissues, and assisting in diagnosis and prognosis of diseases. For example, in [26], the authors introduced a CNN to modify the current pre-trained network for the categorization of brain cancers deploying T1-weighted contrast-improved magnetic quality imaging that has a 96.56% accuracy rate.

Authors in [26], provided a completely computerized three-dimensional CNN technique for classifying glioma brain tumors into low- and high-grade glioma, overriding a pre-processing strategy for strength standardization and adaptive contrast enhancement that demonstrated an authentication precision of 96.49% when applied to the BRATS 2018 dataset. Meanwhile, in [27], the authors developed a mixed model CNN and Neural Autoregressive Distribution Estimation (NADE) to identify brain tumors in MRIs from 3,064 contrast-enhanced T1-weighted images. The experiment was conducted to identify three types of brain cancer, resulting in a 96% accuracy rate. Researchers in [28] developed a fully computerized brain tumor separation and categorization method using MRI scans associated with glioma, meningioma, and pituitary tumors putting into service a CNN. In this work, 3,064 slice imaging samples retrieved from 233 individuals were used and the findings indicated a 97% accuracy rate. In [29], authors applied a BRATS dataset of 577 T1-weighted brain tumors to construct a novel VGG16 network to categorize malignant and benign brain tumors, achieving a 96.7% accuracy.

In [30], researchers utilized MobileNetV2 to build a unique approach for detecting brain malignancies using DL and X-ray images of the brain. Both methods demonstrated an excellent performance, with 92% accuracy. In [31], authors introduced a CNN hybridized classifier approach to provide a classification of brain tumors. In their experiment, the BRATS dataset was employed to evaluate the implementation of the classifier. Specifically, a feedforward NN was used as the input of a hybridized CNN model. The developed CNN model demonstrated better performance compared with other classifiers since it was well-trained. Therefore, adding more epochs will increase the accuracy.

An epoch designates an entire iteration of the architecture, beginning with the input layer and then moving on to the output layer. Authors in [32] presented their DeepTumorNet, a hybrid DL model based on a fundamental GoogLeNet CNN architecture, to classify three types of brain tumor: glioma, meningioma, and pituitary. During the development of the hybrid DeepTumorNet approach, the last five layers of GoogLeNet were deleted, and 15 additional layers were substituted. Moreover, the basic CNN design was unaffected by the substitution of the leaky ReLu activation function. As such, there was a total of 154 layers as opposed to the original 144.

In [33], researchers proposed a differential deep-CNN model for categorizing various types of brain tumor, such as abnormal and normal MRIs. The proposed model can successfully apply contrast calculations to analyze pixel-directional patterns of images and accurately classify massive databases of images without any technical difficulties. The additional differential deep-CNN feature maps that were added to the original CNN feature maps were performed using differential operators.

Authors in [34] integrated both DL and ML techniques to provide a new model for feature extraction and the categorization of brain tumors. Due to their various benefits, both Xception and Inception-v3 were employed for feature extraction, while five different classification techniques were used: softmax, RF, KNN, SVM, and ensemble. For clinical applications involving brain tumors, the Inception-v3 model with softmax was integrated with other models, namely Inception-v3-RF, Inception-v3-KNN, Inception-v3-SVM, and Ensemble. The ensemble technique, Xception-SVM, Xception-RF, and Xception-KNN were all studied deploying this model alongside the Xception model. In [35], researchers investigated the categorization precision of several separated CNN models compared with that of various brain MRI datasets. Here, the standalone CNN model, with 22 layers and a binary category (tumor or no tumor), was again used to teach the CNN model via the transmission DL idea to recognize the tumor subtype.

In [36], authors introduced a novel method for brain tumor detection and classification. In this work, a post-processing method termed linear contrast stretching was utilized to sharpen the edges of the images. Following this, an entropy-based controlled approach and the M-SVM framework were utilized to select the characteristics to identify brain tumors. The MobileNetV2 framework was modified for feature extraction and a 17-layered CNN design was introduced for brain tumor separation. Meanwhile, authors in [37] adopted a CNN to detect the presence of brain tumors, with the main objective being to apply the CNN approach as an ML tool to conduct brain cancer detection and classification. TensorFlow and Keras, two well-known Python libraries, were extensively deployed throughout the training of the CNN model, utilizing a notebook from the open Google Colab platform.

Researchers in [38] explored two different hypotheses using DL models to diagnose brain tumors. A pre-trained DensNet201 DL model was employed for feature extraction of different DensNet blocks. The softmax classifier subsequently classified the brain tumor based on the concatenation of these features. Second, before being delivered to the softmax for brain tumor classification, the characteristics from several Inception modules were extracted from the pre-trained Inceptionv3 model and subsequently concatenated. Both cases were examined implementing the three-class publicly available brain tumor dataset.

Authors in [39] used MRI images to classify three types of brain tumors by introducing a novel hybrid CNN-based architecture integrated with two other techniques. In the initial approach, feature extraction is handled by a pre-trained CNN algorithm GoogleNet model, while pattern categorization is handled by Support Vector Machine (SVM). The latter approach integrates a soft-max classifier with a GoogleNet classifier that has been properly calibrated. Deep pre-trained CNN-based on-transfer learning architectures were compared by authors in [40] in terms of effectively identifying tumors in brain MRI images as benign or malignant. The image classification approach employs transfer learning pre-trained CNN architectures, such as Inception-v3, ResNet50, and VGG16. In the investigation and diagnosis of brain tumors, these methods serve as classifiers. Each testing phase incorporates approaches for theoretically adjusted hyper-parameter integral modification, data pre-processing, and data augmentation.

Researchers in [41] used MRI images to classify three types of brain tumors by two-hybrid approaches. The first method combines unsupervised pattern classification with feature extraction using a pre-trained CNN (i.e., SqueezeNet). Combining supervised soft-max classifiers with finely tuned SqueezeNets is the second approach.

In [42], authors compared seven deep CNN models for the classification of brain tumors based on MRI images. Six pre-trained CNN models were studied (ResNet50, InceptionV3, InceptionResNetV2, Xception, MobileNetV2, and EfficientNetB0). A comparison of all CNN models, including a generic CNN and six pretrained models, showed that InceptionV3 was the most effective CNN model for this dataset. The development of these techniques would benefit clinicians specializing in early brain tumor detection.

Authors in [43] proposed a DL-based Multi-scale Convolutional Neural Network (MCNN) classification model for brain tumors. This method classifies meningioma, glioma, and pituitary tumors using an improved CNN. To ameliorate the CNN model's predictive ability, the authors deployed transfer learning and data augmentation techniques. In addition, mode training and testing are conducted utilizing the cross-validation method holdout.

Researchers in [44] proposed computational-oriented methods to classify brain tumors. A Two-dimensional CNN architecture, convolutional auto-encoder networks, and six ML techniques were proposed for detecting brain tumors. A T1-weighted, contrast-enhanced MRI dataset was used to perform this classification, which included three types of tumors and a healthy brain without tumors.

In [47], authors introduced an ensemble approach to tackle the challenge of lung module detection. In this study, CNN, VGG-16, and VGG-19 were compared. An impressive 95% accuracy was achieved by VGG-16, the built transfer learning model. The dataset includes CT scans with age, modality, and contrast tags, and was compiled from the Cancer Imaging archive. In total, 475 series were collected from 69 patients.

Overall, examining and analyzing the various research articles on DL classification algorithms indicated that the classification is based on ML techniques, while the feature extraction is based on DL models and the used DL techniques to classify and extract features from brain MRIs.

IV. CONCLUSION

This review explored and analyzed the recent techniques used to detect and classify brain tumors in Magnetic Resonance Imaging (MRIs) through the collection, exploration, and analysis of the existing Deep Learning (DL) methods, techniques, and approaches reported in the last four years (2020 – 2024). Five popular search engines were employed to collect the relevant articles. Appropriate inclusion and exclusion criteria were applied to identify the relevant articles for this study.

As previously stated, the main role of DL in brain tumor classification is that it provides an accurate and automated approach to diagnosing and predicting brain tumors. This study discovered that DL can be utilized to analyze MRI images in a far more sophisticated way than traditional methods. This is largely because DL can recognize patterns in the data that traditional methods may have missed. The particular method can also be used to identify and classify tumors more rapidly than traditional methods, leading to more successful treatments. In addition, DL can be deployed to help monitor any changes in a patient's condition over time, assisting doctors in monitoring the patient's progression and deciding how to adjust the treatments and medications more accurately. From a technical perspective, DL can be employed to automate the process of classifying brain tumors. For example, with the use of Convolutional Neural Networks (CNNs), computers can be trained to identify patterns in medical images and develop models that can accurately classify brain tumors. When using DL algorithms, the classification of brain tumors can be carried out more accurately and more rapidly than when utilizing traditional methods.

In comparison to traditional classification algorithms for medical imaging, DL-based methods are currently receiving more attention due to their automatic feature extraction capacity. There is little doubt that many lives can be spared if a tumor is identified and its grade is determined using quick and affordable diagnosis tools. It is imperative to create quick, non-invasive, and economical diagnosis methods and DL techniques could be an important component of that. To the best of our knowledge, only a small amount of research has been conducted in relation to automatic tumor grading using DL techniques, and thus further exploration in this area is required.

After reviewing the relevant literature, some weaknesses of the researchers were found, such as the fact that they did not use the 3D and video datasets. Also, they should have used more than four brain tumor types.

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