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REVIEW

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Deep Learning Techniques for Brain Lesion Classification Using Various MRI (from 2010 to 2022): Review and Challenges

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Abstract: Brain tumors are conditions brought on by the development of aberrant brain cells. They are classified into non-cancerous (benign) and cancerous (malignant). The morbidity and mortality of brain tumors are challenging to determine. A study in the United Kingdom disclosed that around 15 out of every 100 individuals with brain cancer could survive for ten or more years after being diagnosed. The remedial maneuvers of the brain tumors depend upon the kind of brain tumor, degree of cellular abnormality, location of cancer in the brain, and other variables. The treatment decision needs assistance from the deep learning algorithms using magnetic resonance imaging (MRI) data to diagnose brain tumors due to the high dimensionalities of the remedial maneuvers. MRI is a scanning technique that uses strong radio waves and strong magnetic fields to generate detailed images of the body's interior. The study employed deep learning models to detect the tumor region in brain MRI scans, including a convolutional neural network (CNN) model. The proposed processes involved dataset modification and preprocessing, detection, identification, and classification via CNN. Data mining techniques were utilized to uncover significant relationships and patterns from the data, resulting in successful early brain lesion identification and classification using deep learning approaches.

Keywords: brain tumor, brain tumor classification, deep learning, computed tomography, convolutional neural network, magnetic resonance imaging, ResNet

1. Introduction

Most cells in the body grow and then divide in an organized manner to create new cells to maintain the body's health and functionality. Figure 1 shows the pictorial representation of brain lesion. When cells can no longer regulate their growth, they divide too often and randomly; hence every day, our immune system destroys a cell that, had it survived, would have developed into malignant cells (Grampurohit et al., 2020; Kanade & Gumaste, 2015). A tumor is generally a mass of tissue made of extra cells. Cell proliferation that is aberrant and out of control causes brain tumors. According to estimates, 16,500 new lesions in brain were diagnosed in the USA in 2000, accounting for 1.4% of all cancer cases, 2.4% of cancer fatalities, and 20–25% of pediatric malignancies. In the end, brain tumors are thought to cause 13,000 annual fatalities. Approaches for improved segmentation are explored and employed in processing biomedical images (Kanade & Gumaste, 2015).

Deep learning technology is ideal for addressing detections in the field of medicine. The possibility of deep learning technology in the medical field has been a topic of investment. Numerous evaluations that provide a summary of the present state of affairs and a roadmap for future study have been published. Inspired by these findings, we have analyzed several models of brain tumor detection based on deep learning in the suggested survey. In this part, cutting-edge research on brain tumors and deep learning is compared with each other. A comparative analysis of the proposed survey and the current surveys is shown in Table 1.

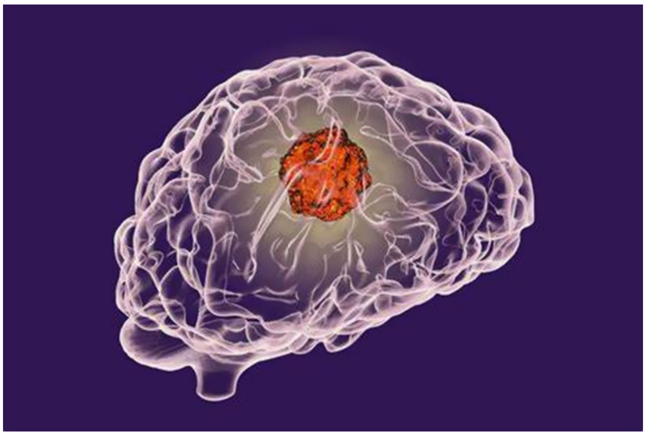

Figure 1. Pictorial representation of brain tumor

Brain tumor segmentation techniques based on machine learning (ML) and conventional image processing are not optimal enough among the currently suggested brain segmentation techniques. Because of this, deep learning-based brain segmentation techniques are more frequently used. The convolutional network model (CNN)

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Table 1. Comparative analysis

Related survey	Year	Objective	Key contributions	Limitations
(Amin et al., 2021)	(Amin et al., 2021)	They cited all relevant academic research on brain tumor detection, its benefits, drawbacks, advancements, and outlook	Majorly focused on the various segmentation, classification, and feature extraction techniques used by researchers	This survey did not clearly describe that all methods successfully detect brain tumors
(Kumar et al., 2022)	(Kumar et al., 2022)	They attempted to find out more about tumor identification in MRI images, incorporating two-stage techniques from 20 research publications published during the last two decades of current century. The comparative study of various processes was also made	This paper looks at various cutting-edge methods for identifying brain tumors. The initial preprocessed segment uses median filtering techniques to preprocess MRI images, and its validation accuracy is 92%. The current approach overcomes various obstacles, including accuracy, tumor quality, and tumor detection time	Improving the accuracy with a low training error rate using various classifier techniques is yet to be done
(Miglani et al., 2021)	(Miglani et al., 2021)	This study reviews about 30 research publications highlighting various state-of-the-art methodologies and analyzed them yielding a complete and comprehensive guide for some particular kind of brain tumor detection, emphasizing the segmentation and classification	The idea of segmenting and detecting brain tumors is presented in this study. Some often employed methods include machine learning techniques like random forests and fuzzy K-means clustering and the widespread usage of CNN. On the MMRI dataset, Krishnakumar and Manivannan (2021) used the MKSVM method to attain the maximum accuracy of 99.7%. Employing a feature extraction technique and CNN in tandem allowed for high classification accuracy of 99.12% (Siar & Teshnehlab, 2019)	Most deep learning techniques classify the tumor region. However, the network is unaware of the anatomical location of the tumor region. Large publicly available datasets are necessary for training deep learning algorithms, and their absence is a barrier
(Al- et al., 2014)	Mohammad Sabbih Hamoud et al. (2014)	This research thoroughly analyzes the approaches and procedures for brain tumor detection using MRI image segmentation. Finally, the report offers a path for the future trends of sophisticated investigations on brain lesion identification and segmentation in a concise discussion at the end	Nowadays, researchers are not concerned with computation speed. To accurately depict the brain tumor, the emphasis is placed on improving the information from images collected from slice orientation and optimizing the segmentation process	Currently, there is no work toward the clinical acceptance of automated methods in this paper
(Bauer et al., 2013)	(Bauer et al., 2013)	By initially offering a quick summary of brain tumors and their imaging, this review will be able to give a thorough understanding. Then, emphasizing gliomas, we evaluate the current state of the art in modeling, registration, and segmentation relevant to brain imaging containing tumors	While segmentation and registration were the main concerns, several registration techniques also incorporated tumor-growth models. Although the initial attempts in this sector were undertaken about 20 years ago, it is clear that recent years have seen the methodologies mature. It is anticipated that their application in clinical practice will rise. Most segmentation techniques work with multi-sequence MRI data, utilizing classification techniques with various characteristics and considering spatial information from a local neighborhood	It became clear during this review that many studies concentrate on segmentation techniques rather than the characteristics derived from the picture. Features may become more crucial when considering the variation in the appearance of various tumor kinds and grades. It could be beneficial to look more closely at pertinent and significant aspects in the future. Investigating how new features might be created to provide better outcomes would be fascinating

favors brain segmentation in the deep learning-based brain tumor segmentation approach.

One of the most challenging tasks in current medical imaging research is the automated identification of brain tumors using magnetic resonance imaging (MRI) images. One of the most crucial and complex aspects of computer-aided clinical diagnostic tools is the segmentation of brain images, which divides the picture into discrete areas to perform automatic detection. Multiplicative sounds are found in brain MRI images, and it is challenging to reduce these disturbances. From a therapeutic standpoint, the noise reduction technique should not ruin the intricate anatomical characteristics. Thus, it makes it tough to separate brain images accurately. Nevertheless, precise segmentation of the MRI images is necessary for the accurate diagnosis made by computer-aided clinical tools (Kanade & Gumaste, 2015).

Medical picture segmentation is necessary for numerous medical applications, including surgical planning, postoperative evaluation, anomaly identification, and more. Despite the abundance of automated and semi-automatic image segmentation methods, most fall short due to the inherent weak borders, poor contrast, and strange and irregular noise seen in medical images (Kanade & Gumaste, 2015).

In recent years, computer-aided diagnostic technology based on ML has been widely applied in medical image analysis (Jiang et al., 2017; Jiang et al., 2019; Qian et al., 2020; Wang & Summers, 2012; Xia et al., 2019). Because the ML-based technique can utilize the different aspects of medical images to train model parameters and then use the learned model to predict, it effectively resolves regression, aggregation, and classification problems in medical images. The model's performance in related tasks can be optimized simultaneously. Deep learning technology can directly extract high-dimensional features from the provided input and automatically adjust the model parameters using back-propagation and forward propagation algorithms. As a result, deep learning technology's application to medical data processing has become a research focus.

1.1. Methodology

1.1.1. Data collection sources

To discover the most recent literary analyses and online resources, we looked through well-known, peer-reviewed journal databases and conferences, including IEEE Xplore, Elsevier, ScienceDirect, Springer, John Wiley, Taylor & Francis, and more. We also used other sources, such as case-specific technical books, concessions, websites for imagining, and online publications relevant to the current study.

1.1.2. Search string patterns

Specific keywords and their synonyms are chosen from the defined research topics to create the search string. The keywords are then arranged with the conditions of "AND" and "OR" in a particular sequence to form the following query: (("Deep Learning" OR "Deep Learning Technology" OR "CNN" OR "Convolution Neural Network") AND ("in the detection of" OR "in the classification of" OR "in the identification of") AND ("Brain Tumor")).

1.1.3. Criteria for inclusion

Following are the inclusion criteria.

- Publication period: 2010–2023.
- Sources: book chapters, journal papers, and certain conference proceedings.
- Keywords related to brain lesion.
- Approaches: Papers focus on the adoption of deep learning technology in the detection of brain tumors.

1.1.4. Criteria for exclusion

Following are the exclusion criteria.

- Papers published before 2010.
- Papers that are not in the English language.
- Papers not focusing on the classification, detection, or identification of brain tumor detection are also excluded.

A total of 575 publications were taken from the database up until the beginning of 2022, as shown in Figure 2. After a thorough assessment, 50 papers that were pertinent to our review paper were finally picked and examined.

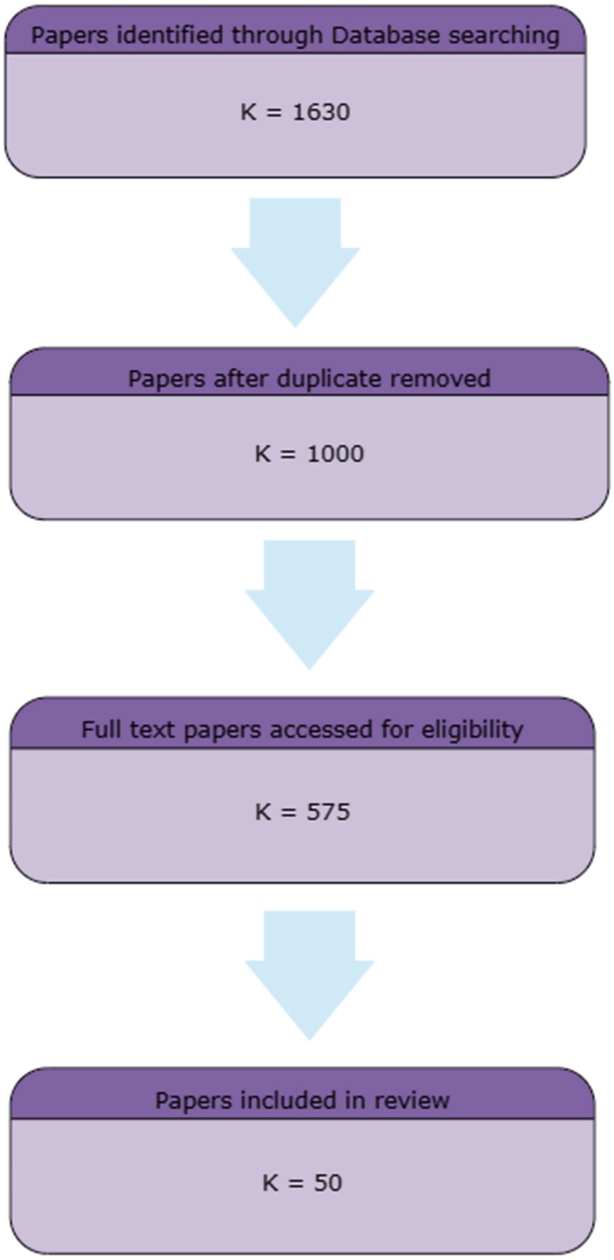


Figure 2. Survey criteria (K = No. of Research Papers/Articles)

1.1.5. Structure of this survey

The structure of this paper is as follows—Section 2 addresses using deep learning technology to manage malignant cell identification. Section 3 covers the overview of human brain anatomy. Section 4 is based on brain image acquisition; Section 5 gives a dataset description; Section 6 provides the taxonomy for adopting deep learning in brain tumor detection; and Section 7 gives the ultimate conclusion. Figure 3 shows the structure of the paper.

We are considering the diversity of image-capturing mechanisms, the class of malignant cells in brain tumors, image-processing techniques, and image-analysis approaches. These are numerous and have been serving humanity in the most acute and severe situations; we have decided to make a brief survey of these methods presenting the pros and cons during the recent period w.e.f. (2010–2022).

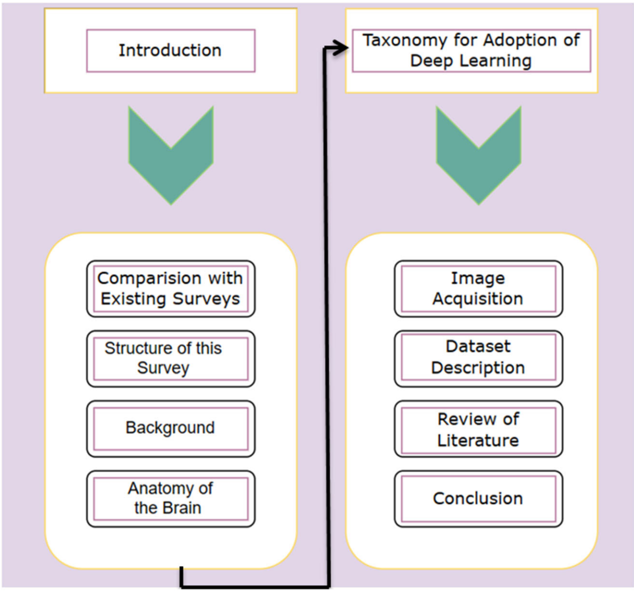


Figure 3. Flow diagram for the survey

2. Background

2.1. Deep learning

Deep learning may be considered as a subset of ML. This is a field where autonomous learning and advancement depend on the study of computer algorithms. Deep learning employs artificial neural networks created to mimic how the brain works, whereas ML uses less straightforward principles. Until recently, the complexity of neuronal networks was constrained by computational capacity. Larger, more complicated neural networks are now possible because of significant data analytics developments, which enable computers to watch, learn, and respond to complex events more quickly than people. Language translation, speech recognition, and image categorization have all benefited from deep learning. Any pattern recognition issue may be resolved with it without the need for human interaction (Reyes, 2023).

2.1.1. Supervised learning

A deep learning process develops a model that produces an open loop chain of expectations for the response to the original dataset or the dataset's unseen images. One kinematics chain connects the impact of the output to the dishonorable. The connections are bound in the case of parallel exploiters, creating a closed loop chain. The component that makes the effect may be located at the end of the chain, but it is connected to the base by at least two or more kinematics chains. As a result, none parallel manipulators might profit from more elastic and wider occupied planets compared to parallel manipulators (Yan et al., 2015).

2.1.2. Unsupervised learning

Unsupervised learning is a method that falls under the umbrella of ML. It is not necessary to oversee the model in unsupervised learning. Alternatively, one must let the model run autonomously to gather data. It essentially functions with unlabeled data. Compared to supervised learning, algorithms for unsupervised learning enable more complex processing. It may be more impulsive when comparing unsupervised to spontaneous learning methods (Al-Massri et al., 2018; Al-Mubayyed et al., 2019).

2.2. CNN

ConvNets, often called convolutional neural networks or CNNs, are considered one of the most critical classes for identifying and categorizing images. CNNs are often employed in various applications, including object identification, face recognition, picture categorization, etc. To build and train CNN, researchers occasionally use Python libraries (pandas, OpenCV, tensorflow, Keras, etc.) or Matlab (Al-Mubayyed et al., 2019; Barhoom et al., 2019).

2.3. Pituitary brain tumors

Pituitary brain tumors are abnormal growths that occur in the pituitary gland. Many hormones that regulate essential bodily functions like growth and development, organ function (breasts, kidneys, and uterus), and gland function (gonads glands, adrenal, and thyroid) are produced from specific pituitary tumors. Specific pituitary tumors may cause one's pituitary gland to yield fewer hormones. The most common pituitary tumors are benign growths. Adenomas do not spread to other body parts; they remain contained to the pituitary gland or tissues nearby. Pituitary tumors are uncontrolled pituitary gland growth (Kleihues et al., 2002; Landis et al., 1998).

2.4. Glioma brain tumor

Gliomas are a kind of tumor that can grow in the brain or spinal cord. The gliomas begin in the adherent support cells that surround nerve cells and help them carry out their activities. Tumors can develop from one of three glial cell types. In addition to the tumor's hereditary topographies, gliomas are classified according to their share of glial cells. Thus, it can help anticipate how the cancer will behave over time and potential treatment strategies (Kleihues et al., 2002; Landis et al., 1998).

2.5. Meningioma brain tumor

A meningioma is a tumor from the films encircling one's spinal cord, brain, or meninges. Although it is not technically a brain tumor, it falls under this category since it may cushion or compress the neighboring brain, blood vessels, or nerves. A meningioma is the most prevalent type of tumor that develops in the head (Landis et al., 1998). Meningioma brain tumor examples are shown in Figure 4.

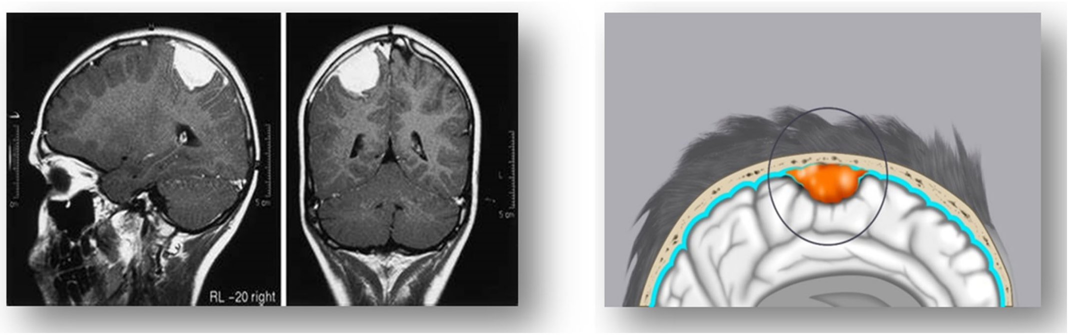


Figure 4. Meningioma brain tumor images

2.6. Pre-trained deep learning models

2.6.1. RESNET-50

One MaxPool layer, one average pool layer, and 48 convolution layers make up the ResNet-50 model. There are 3.8 × 109 floating point operations available. Figure 5 shows the architecture of ResNet-50. Kaiming created ResNet-50 with the intention of residual learning, which can be easily interpreted as deriving input properties from a particular layer. ResNet may do this by directly connecting the input of the kth layer to the (k + x)th layer using shortcut acquaintances for each pair of the 33 filters. The goal of manually avoiding layers is to keep the undesirable vanishing gradients away by repeatedly utilizing initiations from the last layer until the surrounding layer has learned its weights (Dheir et al., 2019). Weights are adjusted to maintain the preceding layer while enhancing the adjoining layer during the artificial neural network training.

Shahid et al. (2022), Sahaai et al. (2022), and Chatterjee et al. (2022) used ResNet-50 architecture in their respective research work.

2.6.2. RESNET-101

ResNet-101 is a variant of the 50-layer ResNet model and is a 101-layer residual network. Training increasingly complex neural networks is more challenging. It offers a residual learning framework to simplify training networks more profoundly than previously employed ones. Instead of learning unreferenced functions, it deliberately reformulates the layers to understand residual processes concerning the layer inputs. On the ImageNet dataset, we test residual networks up to 152 layers deep, eight times deeper than VGG nets, while less complicated.

A CNN that is 101 layers deep is called ResNet-101. The ImageNet database contains a pre-trained version of the trained network on more than one million images. Figure 6 describes the structure and the block diagram of ResNet-101.

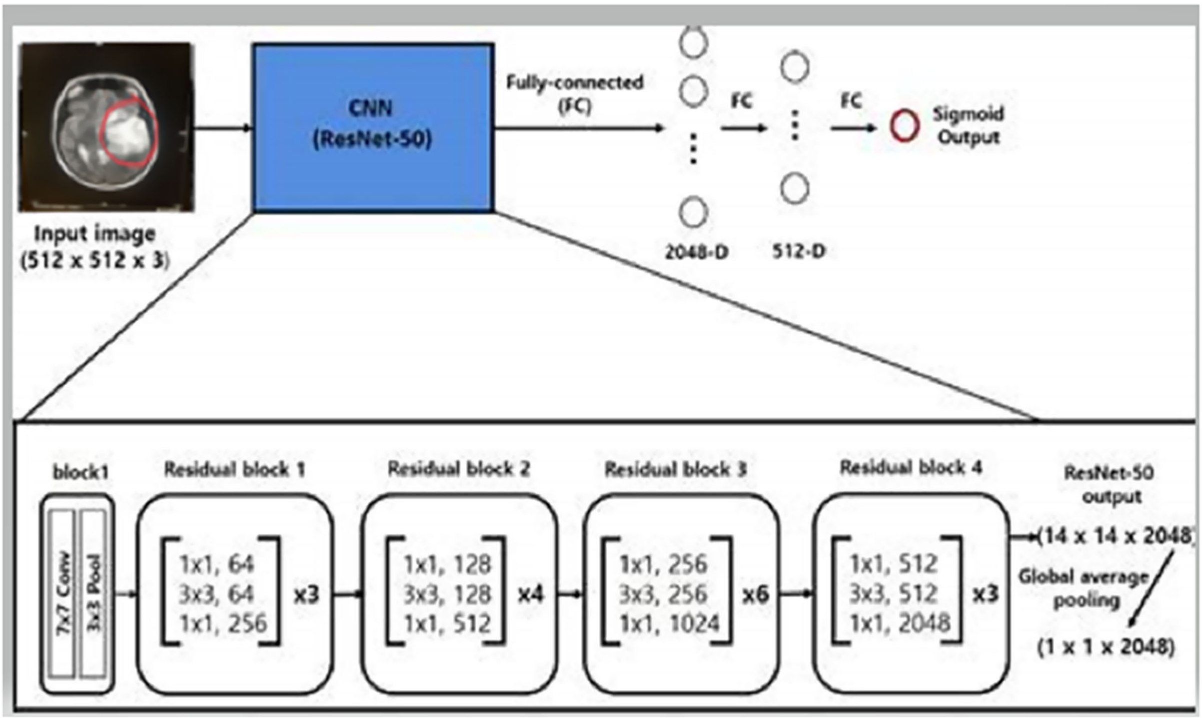


Figure 5. Architecture of ResNet-50

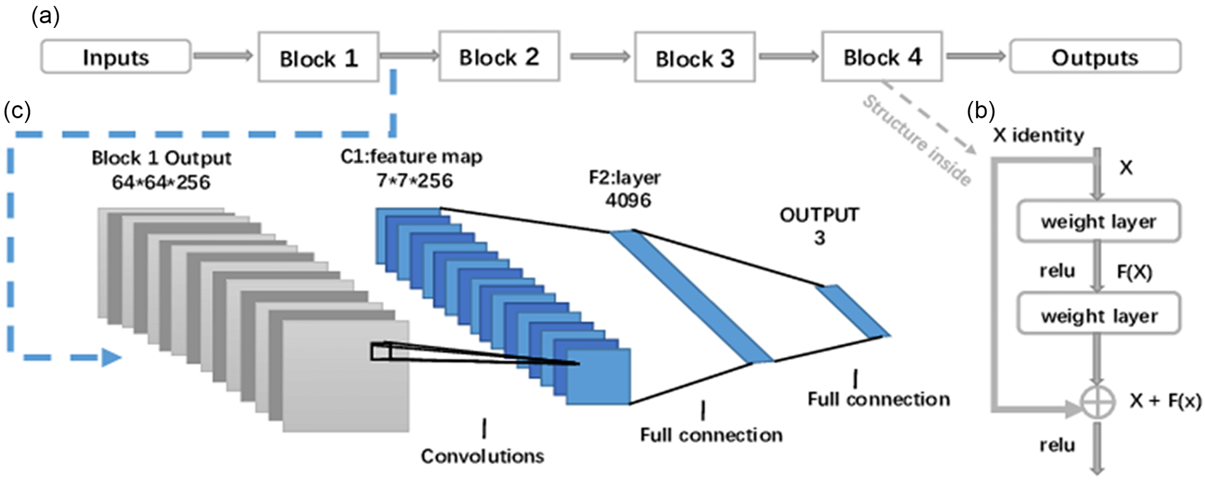


Figure 6. ResNet-101. (a) Structure. (b) Block diagram

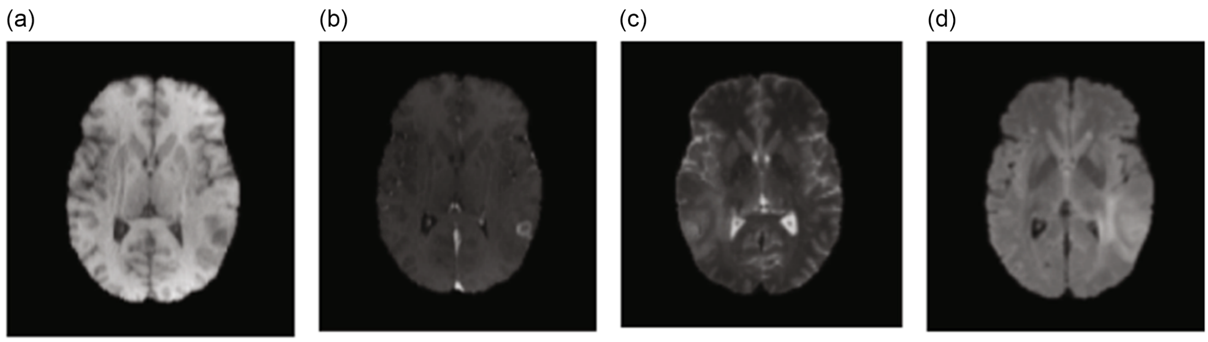


Figure 7. Glioma MRI. (a) T1w, (b) Postcontrast T1w, (c) T2w, and (d) FLAIR

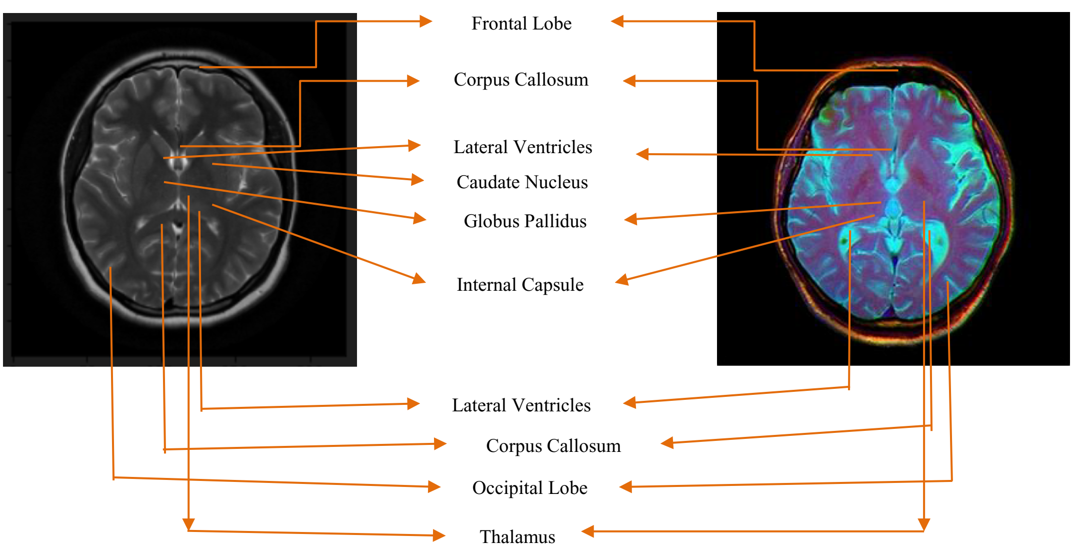


Figure 8. Human brain overview structure, left side: axial slice MRI, right side: color-coded version of image (Amin et al., 2021)

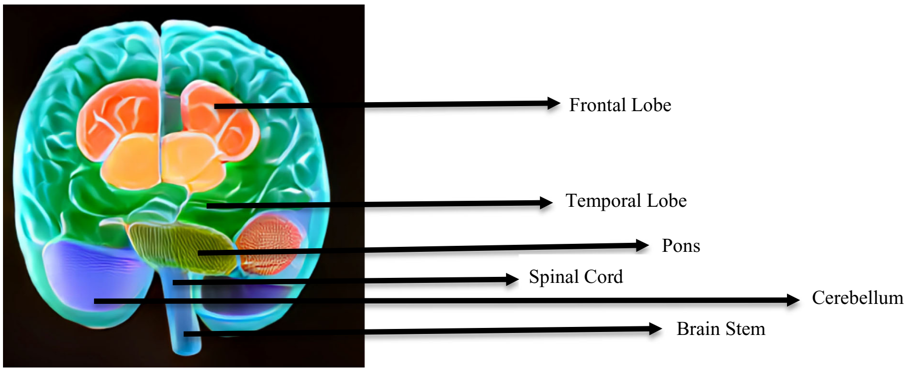


Figure 9. The major subdivision of the human brain (Amin et al., 2021)

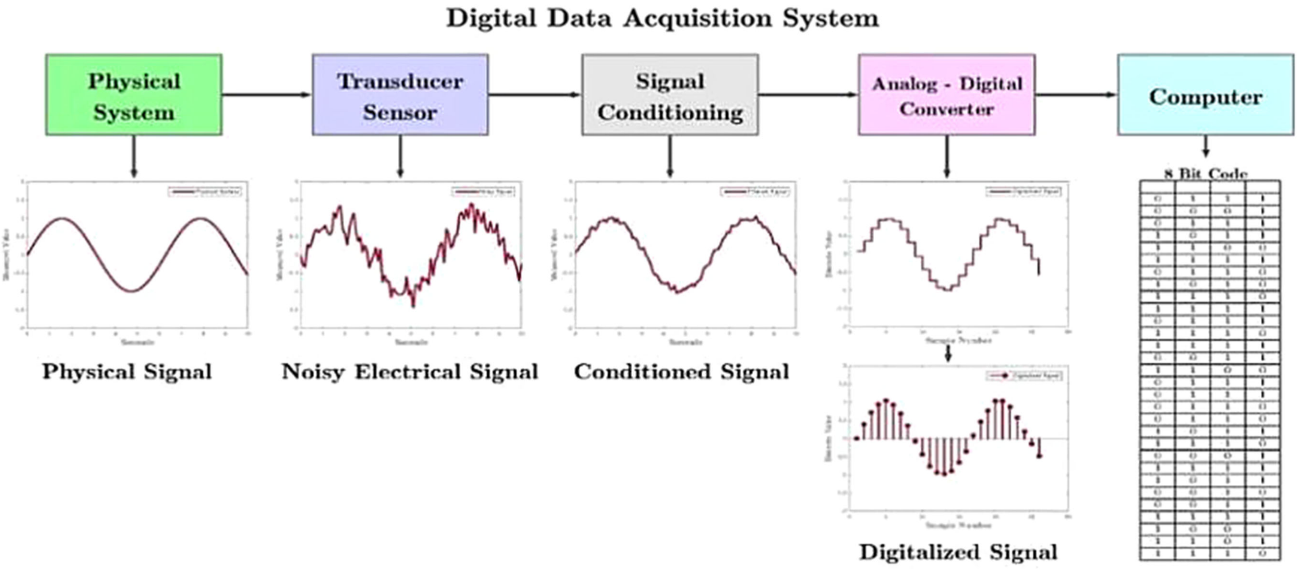


Figure 10. Digital data acquisition system block diagram

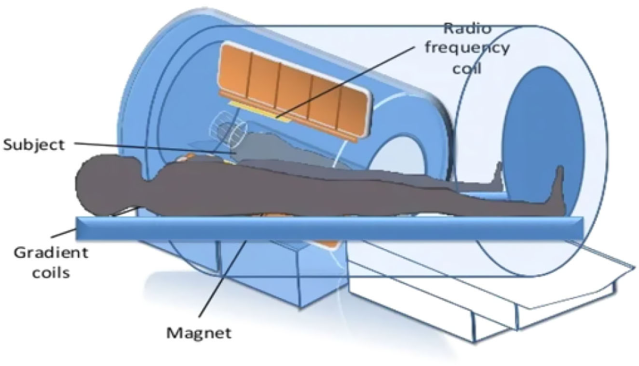


Figure 11. Overview of MRI system

Ghosal et al. (2019) and Gupta (Jatin, 2022) used ResNet-101 architecture in their respective research work.

2.7. Magnetic resource imaging

This is a crucial technique for accurately diagnosing, treating, and monitoring the disease because it offers extensive information on brain tumors' architecture, cellular composition, and vascular supply. Medical professionals can identify and treat medical disorders using MRI, a noninvasive medical procedure. Using a radio frequency pulses, a computer, and a strong magnetic field, MRI creates precise images of bones, soft tissues, organs, and almost all other internal body components.

Figure 7 illustrates how different tumor tissues may be seen using various MRI sequences (Bauer et al., 2013). Four modal rows are frequently utilized in MRI imaging of gliomas: T1-weighted, post-contrast T1-weighted, T2-weighted, and fluid-attenuated inversion recovery (FLAIR). Sequence variations reflect the diversity of glioma tissues (Gillies et al., 2016). Edema tissues may be observed using the overall FLAIR sequence, and the active tumor core components can be seen using the T1ce sequence.

Brain MRI is a multimodal and many-layer three-dimensional scan picture. Additionally, manual segmentation frequently bases area segmentation on the brightness of the view seen by the

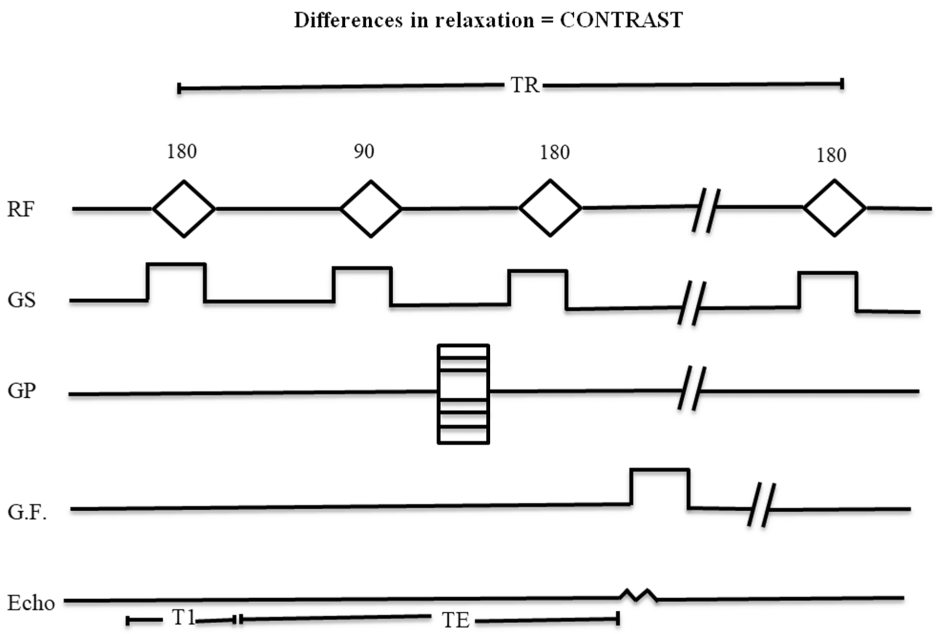
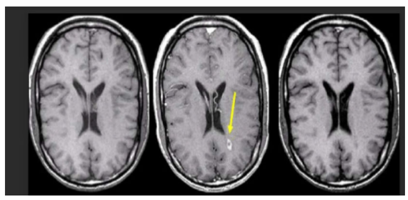
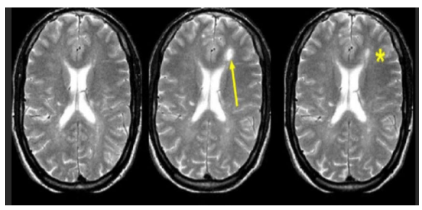
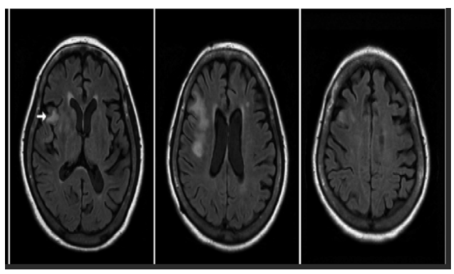


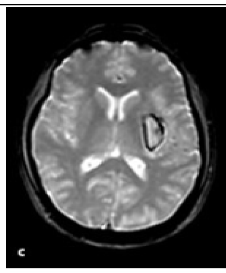
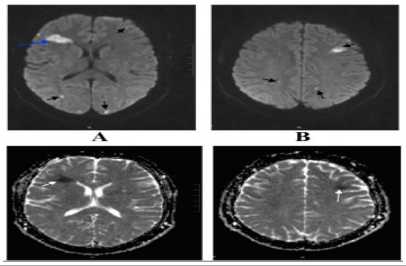
Figure 12. Generation of MRI sequences

Table 2. Image configuration outline

S. no	Type of image	Clinical specification	Useful for	Example
1.	T1 weighted	Tissue with high water content will appear dark (grey). Tissue with low water content will appear as brighter. A T1 weighted depends on the longitudinal relaxation of a tissue's net magnetization vector (NMV)	In anatomic details, we can pick up vascular changes + contrast and disruption of blood–brain barrier + contrast	
2.	T2 weighted (Radiopaedia.org, 2021)	High water content tissue will have a brighter appearance. Tissue with low water content will appear dark (grey). The transverse relaxation is what a T2 weighted depends on (also known as "spin-spin" relaxation).	Anatomic details (especially for CSF spaces) We can pick up most lesions and cannot distinguish lesions from CSF	
3.	FLAIR *(fluid attenuation inversion recovery)* (Radiopaedia.org, 2023a)	Same as T2 weighted except for free-flowing water (CSF) is dark. Non-free-flowing water is bright. Fat is dark.	Same as T2, but it does a better job in delineating lesions near ventricles because edema would be dark, and it does an excellent job differentiating between grey and white	

(*Continued*)

Table 2. (*Continued*)

S. no	Type of image	Clinical specification	Useful for	Example
4.	GRE *(gradient echo (SW1, T2*))* (Tang et al., 2014)	Paramagnetic substances (blood, calcium, and other metals) are dark	Early hemorrhage and old hemorrhage are easily recognizable	
5.	DWI *(diffusion-weighted imaging)* (Radiopaedia.org, 2023b)	Fluid restriction is bright (cytotoxic edema) Must correlate these findings with ADC (apparent diffusion coefficient) • Fluid restriction is dark	Ischemia, abscess, and seizures	

human eye, which is easily influenced by the caliber of image creation and the personal factors of the tagger. It is prone to inaccurate segmentation and redundant area segmentation. Therefore, a completely automated segmentation approach for gliomas with excellent segmentation accuracy is required in clinical practice (Wu et al., 2020).

3. Overview of the Anatomy of the Brain

A person can adapt to and endure a variety of environmental settings because to the highly evolved human brain, which serves as the control center for all bodily organs. The human brain enables verbal communication, motor function, and the sharing of ideas and emotions. To comprehend the goal of this study, the tissue structure and the anatomical components of the brain are discussed in this section (Al-Tamimi & Sulong, 2014). Figures 8 and 9 represent the human brain overview and major brain subdivisions, respectively.

The brain is composed of two types of tissues: grey matter (GM) and white matter (WM). Neuronal and glial cells, sometimes referred to as neuroglia or glia, make up the basal nuclei, the GM nuclei located deep inside the white case. These cells control brain activity. The putamen, caudate nucleus, claustrum, and pallidum are among the basal nuclei. Axon-rich WM fibers link the cerebral cortex to other brain regions. Connecting the left and right hemispheres of the brain is a significant band of WM fibers called the corpus callosum. Cerebrospinal fluid, which includes salts, enzymes, white blood cells, and glucose, is also present in the brain. This fluid moves via ventricles around the spinal cord and brain to protect them from harm. Another kind of tissue is the meninges, a membrane covering the brain and spinal cord (Noback et al., 2005).

3.1. Brain tumors

Under some circumstances, brain cells proliferate and multiply uncontrollably because the system that controls average cell growth cannot prevent brain cell development for various reasons. A brain tumor is generally an abnormal mass of brain tissue that takes up space in the skull, interferes with normal brain activities, and puts pressure on the brain. Some brain tissues are moved, pushed up against the head, or are to blame for nerve damage in other healthy brain tissues as a result of increasing pressure on the brain. Numerous brain tumor kinds have been classified by scientists based on factors such as location in the brain anatomy, the type of tissue involved, and whether has the potential of carcinogenesis and certain other factors (Buckner et al., 2007). The World Health Organization classified brain tumors into 120 separate categories. Based on the cell's origin and behavior, it is categorized into less aggressive and more aggressive groups. Tumor states are also categorized, ranging from grades I (least malignant) to IV (more malignant). This indicates the rate of growth, despite variations in grading schemes based on the kind of tumor (Louis et al., 2007).

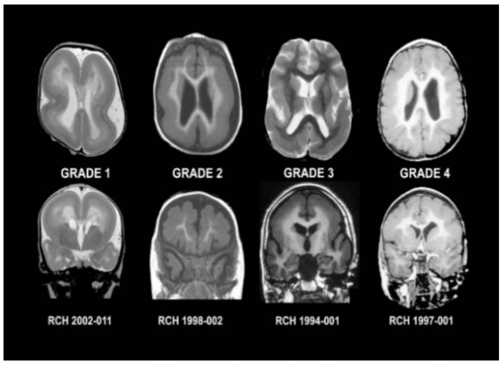
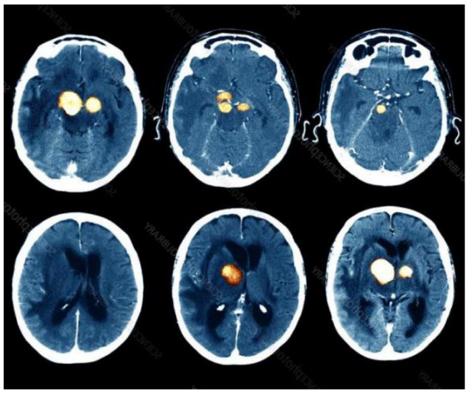
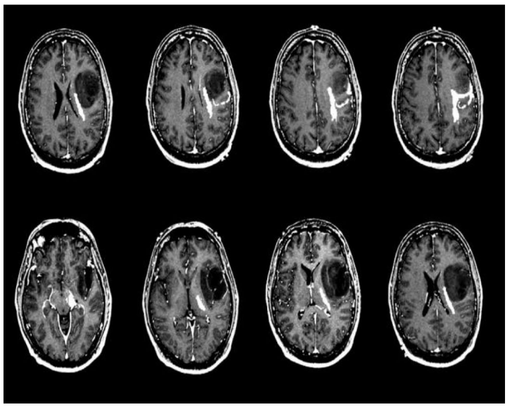
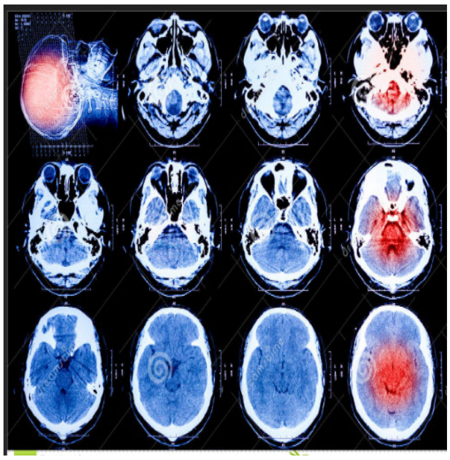
4. Brain Data Acquisition

Data acquisition is the process of sampling signals that measure actual physical conditions and converting the resulting samples into digital numeric values that a computer can analyze (Paszkiel, 2020). Figure 10 shows the data acquisition system.

4.1. MRI images

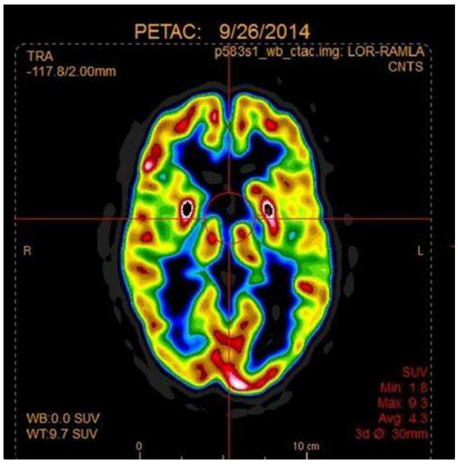
An MRI sequence is a sequence of events inside the machine that gives us our image, Figure 11.

Table 3. Various types of scans

<table>
<tr><th>TYPE of scan</th><th>Specifications</th><th>Example</th></tr>
<tr><td>MRI</td><td>The use of MRI is widespread. Finding issues, including tumors, bleeding, injuries, blood vessel illnesses, or infections, is done using this method. An X-ray, ultrasound, PET, or CT scan may be followed up with an MRI to learn more about an issue. During an MRI, contrast material may be utilized to display aberrant tissue (Kanade & Gumaste, 2015).
Additionally, MRI may provide much physiological tissue information and exhibits considerable soft tissue contrast features. MRI is often utilized to identify gliomas intraoperatively, preoperatively, and postoperatively. A glioma is a tumor of edematous tissue, a tumor-active margin, and a necrotic core. Medical professionals can assess different body areas and identify certain disorders. They can identify and treat medical conditions using magnetic resonance imaging, a noninvasive medical procedure that does not require ionizing radiation</td><td>
</td></tr>
<tr><td>CT scan</td><td>A CT scan of the brain is a non-invasive diagnostic imaging procedure that uses precise X-ray measurements to produce horizontal or axial pictures, often known as slices, of the brain. Brain CT scans can provide more accurate information on the structure and tissue of the brain than standard head X-rays, which can provide greater insight into brain diseases and traumas. During a brain CT scan, the X-ray beam revolves around the body to provide several pictures of the brain. It is possible to do CT brain scans with or without "contrast." Contrast is a substance that can be injected intravenously (IV) or taken orally to increase the visibility of the particular organ or tissue under study. The skull and spine, two bone components close to a brain tumor, may be seen in greater detail on a CT scan</td><td>
</td></tr>
<tr><td>X-rays</td><td>X-rays create images of the skull using invisible electromagnetic energy beams. Body tissues are exposed to X-rays on specially prepared plates (similar to camera film). A "negative" image of some sort is created. A structure will seem whiter on the film the more solid it is. Different bodily components let various quantities of the X-ray beams pass through when the body is exposed to X-rays
The quantity of X-rays that pass through the tissues determines how bright or dark the images are. Most of the X-ray energy may pass through soft tissues in the body, including blood, skin, fat, and muscle, making them look dark grey in the image. Few X-rays can travel through a bone or tumor because they are denser than soft tissues, so they look white on the X-ray. The X-ray beam passes through the fractured portion of a bone when it breaks, leaving a dark line in the otherwise white bone</td><td></td></tr>
</table>

(*Continued*)

Table 3. (*Continued*)

TYPE of scan	Specifications	Example
PET	A positron emission tomography (PET) scan is an imaging procedure that can determine how our organs and tissues operate biochemically or metabolically. A radioactive substance (tracer) is used in the PET scan to display both regular and aberrant metabolic activity. Before a sickness manifests on another imaging test, such as a CT scan or a PET, MRI scan may frequently detect the aberrant metabolism of the tracer in disorders (MRI) Most frequently, the tracer is injected into a vein in our hand or arm. The tracer will then gather in our body's regions with greater metabolic or biochemical activity, frequently identifying the disease's location. PET-MRI or PET-CT scans are the terms used to describe combining PET images with CT or MRI	

So, each pulse sequence consists of two essential components:

$$\text{Pulse sequence} = \text{Radio frequency} + \text{Acquisition phase}$$

4.1.1. How MRI sequences are created

- Give energy (excite proton spin): – We give energy to our system or tissue. So, we excite proton spins using RADIO FREQUENCY ENERGY.
- Turn off that source of energy.
- Observe the energy we get back from that excited tissue due to the relaxation of proton spins (back into alignment with the magnet). Figure 12 depicts how differences in relaxation give different contrast.

Most MR methods may produce high-resolution images. However, other imaging methods exhibit unique contrast, are sensitive to specific tissues or fluid areas, and highlight brain tumors' pertinent metabolic or biophysical features. The datasets in Table 2 include T1-weighted, T2-weighted, FLAIR, contrast-enhanced T1-weighted, dynamic contrast-enhanced MRI, and diffusion-weighted imaging (DWI) sequences. In academic and clinical settings, the T2w, T1w, FLAIR, and ceT1w sequences are often used to classify brain tumors. Each row may be identified by a specific pattern of magnetic field gradients and radiofrequency pulses, which produces images with a distinctive look. Based on data from Johnson (2022); Radiopaedia.org (2023a), Table 2 outlines the imaging configurations and the primary clinical differences of GRE, T2w, DWI, T1w, and FLAIR.

4.2. MRI vs. CT scan, PET, X-rays Table 3

5. Dataset Description

Table 4 below describes the various dataset used in this work area.

6. Review of Literature

This section presents a detailed overview of the research papers on brain tumor classification using various techniques published from 2018 to 2022 in Table 5 and from 2010 to 2017 in Table 6.

6.1. Advantages of implementing deep learning algorithms

The approaches used to separate brain tumors may be broadly categorized into three groups: deep learning (Dvořák & Menze, 2016; Havaei et al., 2017; LeCun & Bengio, 1995; Pereira et al., 2016; Zhang & Sejdić, 2019; Zikic et al., 2014), ML (Bauer et al., 2011; Geremia et al., 2012; Khotanlou et al., 2009; Le Folgoc et al., 2016), and classic imaging algorithms (Deng et al., 2010; Gooya et al., 2012; Jayadevappa et al., 2009; Kwon et al., 2014; Prastawa et al., 2004; Stadlbauer et al., 2004). Due to its remarkable accuracy, deep understanding has recently taken the lead as the technique of choice for complex problems. The CNN suggested in LeCun & Bengio (1995) has come a long way in image processing. As a result, the CNN-based segmentation approach is frequently employed in segmenting lung nodules, retinal segments, liver cancer segments, and glioma segments (Zhang & Sejdić, 2019).

Table 4. Detailed dataset description

S no.	Dataset name	Dataset details	Dataset used in	Approach used	Features selected	Performance
1.	Brain lesion dataset from Figshare	3064 T1-weighted contrast-enhanced images are from 233 patients with three different brain tumors	(Cheng et al., 2016)	To include useful contextual information, they first enhance the tumor region and utilize it as the region of interest. Second, they use an adaptive spatial division strategy based on intensity orders to partition the increased tumor area into subregions. Third, they combine these per-subregion vector representations using the Fisher kernel framework to create an image level (Cheng et al., 2016)	(1) The number (N) of pooling regions, (2) the radius (R), (3) the size (W) of raw image patches, (4) the reduced dimensionality (D), and (5) the number (K) of vocabulary size.	Mean average precision obtained at 94.68%
2.	RIDER dataset	MRI-multi-sequence images of 19 glioblastoma patients are present	(Irmak, 2021)	CNN consists of 13 weighted layers: 1 input layer, two convolutional layers, 2 ReLU layers, 1 normalizatio*n* layer, 2 max-pooling layers, 2 fully connected layers, 1 dropout layer, 1 softmax layer, and 1 classification layer	Not Mentioned	99.33% accuracy
3.	The Repository of Molecular Brain Neoplasia Data	MRI multi-sequence scans from 130 individuals with grade IV, grade III, and grade II gliomas are included in the REMBRANDT dataset. This collection has 110,020 images in total (Abhilasha et al., 2022)	(Irmak, 2021)	CNN, 25 weighted layers: 1 1, 6 convolutions, 6 ReLU activation, 1 normalization, 6 max pooling, 2 fully connected, 1 softmax, 1 dropout, and a classification layer	Not Mentioned	92.66% accuracy
4.	Cancer genome atlas low-grade glioma (TCGA-LGG)	There are 241,183 MRI scans from 199 individuals with grade I and II low-grade gliomas in the TCGA-LGG dataset	(Irmak, 2021)	CNN 16 weighted layers: input, 3 convolutions, 3 ReLU, 1 normalization, 3 max pooling, 2 fully connected, 1 dropout, 1 softmax, and 1 classification layer	Not Mentioned	98.14% accuracy
5.	IXI Dataset (Imperial College London, n.d) and Cancer Imaging Archive Datasets (Clark et al., 2013)	Almost 600 MR images of healthy, normal people. Each subject's MR image capture procedure includes the following: images with T1, T2, and PD weighting, MRA images, images with diffusion weighting (15 directions)	(Anaraki et al., 2019)	CNN with genetic algorithm	Features are extracted automatically to save time.	In the first case study, three glioma grades could be classified with 90.9% accuracy. In an alternative case study, 94.2% of the tumor types—glioma, pituitary, and meningioma—were correctly recognized
6.	BRATS MICCAI Brain tumor Dataset	T1, T2, T1Ce, and flair sequences. Every volume has 155 slices. 155 slices are for one volume, 210 volumes are HGGs, and 75 volumes are in another type of glioma	–	–	–	–
7.	MICCAI's Dataset on Brain Tumor Segmentation (year 2019) (Bakas, 2020)	a) Post-contrast T1-weighted (T1Gd), b) T2 fluid attenuated inversion recovery (T2-FLAIR) volumes, c) native (T1), d) T2-weighted (T2)	–	–	–	–

Table 5. Review from 2018 to 2022

S. No.	Journal/paper year	Methodology	Advantages	Disadvantages
1.	(Anand et al., 2021)	3D-fully CNN is used for segmenting brain tumors	The network performed well on complex examples as hard mining is introduced in this paper	The proportion of HGG and LGG in the used datasets is unknown
2.	(Badža & Barjaktarović, 2020)	New CNN architecture is used	A designed neural network is more straightforward than pre-existing neural. Since we used whole images as input, no preprocessing or tumor segmentation was required	Database augmentation is not done, i.e., the dataset used is small
3.	(Amin et al., 2020)	An automated system is presented for detecting a brain tumor at the lesion and image levels	Able to differentiate between the two types of tumors, i.e., cancerous and non-cancerous. The method achieved 0.98 area under the curve, an average of 97.1% accuracy, 98.0% specificity, and 91.9% sensitivity	The system is tested on MRI
4.	(Wu et al., 2020)	SVM and deep CNN	Segmentation, less time is required	An algorithm is not optimized
5.	(Deepak & Ameer, 2019)	GoogLeNet and deep CNN	Improved performance and robustness	Poor performance of the transfer model
6.	(Saleh et al., 2020)	Convolutional neural networks	Our brain tumor dataset trained five pre-trained models—MobileNet, VGG16, InceptionV3, Xception, and ResNet-50. 97.25, 97.50, 98.00, 98.75, and 98.50% were the respective F1-scores for unseen images Early tumor diagnosis is made to prevent physical side effects like paralysis and other impairments	Data augmentation is a must step to overcome the limitation in images of the dataset
7.	(Suhara & Mary, 2018)	CNN, KNN, and SVM	Complexity and computation time are low, and accuracy is high	Training time is high
8.	(Naseer et al., 2021)	CNN	CNN performance is improved using techniques for augmented geometrical and statistical data on brain tumor MRI	Variations of CNN are excluded in this paper
9.	(Asodekar & Gore, 2019)	SVM, random forest, image processing technique	Image-processing methods are employed to segment brain tumors, and shape-based features are extracted for feature extraction. To identify benign and malignant brain tumors, extracted shape-based characteristics are fed to ML algorithms such as SVM and random forest algorithm	The task of automatic brain tumor segmentation at the practical level is still pending
10.	(Dora et al., 2018)	A hybrid methodology is used	A subset with *N* significant training feature vectors is used for precise classification. Utilizing the *m*, *n* layered cross-validation approach, the value of *N* is optimized	The model is plagued with repetition of the training samples resulted in overfitting, biased findings, and underfitting
11.	(El-Melegy and El-Magd, 2019)	Random forest classifier	Five random forest classifiers were used to classify a unique class, and all classifiers were trained in a two-class fashion. Experimental results showed an outstanding improvement in segmentation for all three tumor sections	It was mainly focused on random forest classifiers for increasing accuracy
12.	(Krishnakumar & Manivannan, 2021)	MKSVM algorithm, K-means clustering algorithm	MRI scans were preprocessed before segmentation, and the feature extraction technique was carried out with the preprocessed images. An enhanced Gabor wavelet modification was used to retrieve the features. This study introduced a segmentation approach known as rough *K* means clustering	Every step is dependent on the previous procedure of the steps

(*Continued*)

Table 5. (*Continued*)

S. No.	Journal/paper year	Methodology	Advantages	Disadvantages
13.	(Chandra & Bajpai, 2020)	Fractional partial differential equation	Fractional calculus was employed to attain the precision that supplied a derivative with an indefinitely ordered offshoot. A mesh-free approach was utilized to solve the suggested equation to provide a better and faster solution	Due to the level set method in the segmentation step, it took a long time
14.	(Pitchai et al., 2021)	Fuzzy K-means clustering, deep learning, ANN	A model using the combination of the ANN and the fuzzy K-means algorithm was presented for brain tumor segmentation. The total accuracy of the procedure was 8% higher than the K-nearest neighbor methods	Classification performance is based on the number of hidden neurons
15.	(Rajan & Sundar, 2019)	Fuzzy K-means clustering, deep learning	Since the KMFCM has a short execution time and can handle many segmentation issues, it was recommended The model was examined based on the number of white and black pixels, processing speed, and the region where tumors could be seen	The considered dataset is small
16.	(El Kader Isselmou et al., 2019)	Deep learning, CNN	The suggested design was evaluated using MRI scans to identify patients with distinct types of cancers	5 MR brain images are required to fetch the results
17.	(Kumar & Mankame, 2020)	Dolphin SCA algorithm	Deep CNN, a deep learning technique, was proposed based on dolphin-SCA. The procedures used were preprocessing, segmentation, feature extraction, and classification	The suggested method is implemented using a computer running Windows 10 with an Intel CPU clocked at 2.16 GHz and 2 GB of RAM The approach is put into practice in MATLAB
18.	(Siar & Teshnehlab, 2019)	Feature extraction algorithm, CNN Softmax	The feature extraction algorithm and CNN were combined to classify and segment. The accuracy of CNN was determined using the RBF and the DT classifiers	From a total of 226 test data photos, three were incorrectly diagnosed
19.	(Hu & Razmjooy, 2021)	ISOA algorithm, DBN, SVM	It was suggested to use an automated technique to identify brain tumors	The training set requires additional memory for efficient processing. The technique used in this paper is quite time-consuming, and all the available data are input simultaneously
20.	(Lei et al., 2021)	Sparse-constrained level set algorithm	With the help of the method described in this research, a sparse representation model of a brain tumor's shape was created. It created a way for energy to function based on a level set	The input image must be registered before moving on to the next step
21.	(Byale et al., 2018)	The Gaussian mixture model is used to determine the region of interest	Machine learning techniques outperformed traditional machine learning methods in precision, specificity, and sensitivity, accuracy, scoring 94.44, 96.6, 93.33, and 93.33% higher in each case	Since the size of a patient's brain tumor changes over time, identifying and categorizing the tumor from enormous datasets becomes difficult and time-consuming. Big datasets cannot be trained with this technique
22.	(Varuna et al., 2018)	A noise removal technique is developed for extracting gray-level co-occurrence matrix features	This method had a better classification accuracy of 95%	It takes longer to complete activities like segmenting, identifying tumors from MRI scans, and determining the contaminated region. Additionally, using conventional image-processing techniques, aberrant brain structures are difficult to discern
23.	(Bhanothu et al., 2020)	R-CNN, RPN	The primary layer for the suggested networks was VGG-16, a CNN design. This research study can be expanded to calculate the tumor's percentage area concerning the human brain region	Fast R-CNN tends to be very accurate, but the biggest problem is that they are incredibly slow

24.	(Shakeel et al., 2019)	Machine learning-based back propagation neural networks (MLBPNN)	The imerode function is used, which helps us to locate the tumor precisely	Some geometric information is lost due to the use of 2D image segmentation methods
25.	(Chatterjee et al., 2022)	Two spatiotemporal models are used, ResNet (2+1)D and ResNet mixed convolution	This model achieved a test accuracy of 96.98% and a macro F1 score of 0.9345. It is also the most computationally efficient model	It only uses T1 contrast-enhanced images for classifying the tumors, which already resulted in good accuracy
26.	(Rizwan et al., 2022)	Gaussian convolutional neural network (GCNN)	Worked on two different datasets: One of the datasets categorizes tumors into meningioma, pituitary, and glioma. The other distinguishes between the three glioma classes: grades II, III, and IV. The former achieved an accuracy of 99.8%, and the latter gained 97.14%	Only T1-weighted images are used in both datasets
27.	(Irmak, 2021)	Three different CNN models are used	Grid search is used to adjust nearly all hyper-parameters automatically	- -
28.	(Anaraki et al., 2019)	CNN is evolved using genetic algorithm	Bagging is used as an ensemble approach to reduce the variation of prediction error	Genetic algorithm takes a lot of time and is expensive computationally
29.	(Methil, 2021)	Computer vision along with SOM (self-organized map)	In this study, CNN attained an impressive recall of 98.55% on the training and 99.73% on the validation set	Image preprocessing can occasionally damage the information that causes a tumor image to appear as a non-tumor image in the CNN model's eyes. The input image needs to be a suitable size because if it is not, it will need to be resized to the extent we specified in the image augmentation stage
30.	(Shah et al., 2022)	A deep CNN EfficientNet-B0 is a base model	An efficient model was developed which claims high accuracy	- -
31.	(Maram & Rana, 2021)	U-Net architecture is used	Compared to other architectures, the model's validation accuracy of 98.411% and a training accuracy of 98.485% are deemed better results	Residual network implementation in conjunction with the U-Net model on the BraTS2020 dataset can improve accuracy, and 3D U-Net architecture can lead to improved accuracy compared to the U-Net framework designed for estimating tumors in 3-dimensional biological images
32.	(Sangeetha et al., 2020)	ResNet-50	GoogleNet, ResNet, and VggNet. GoogleNet reports more accuracy at 93.45%, ResNet at 96.50%, and VggNet at 89.33%. Ultimately, it is demonstrated that ResNet-50 produces results 10% faster and 10% more accurately than VggNet and GoogleNet	The paper offered various classification techniques based on the number of iterations
33.	(Shahid et al., 2022)		Unlike basic KNN, and SVM which provided 78 and 85% accuracy on the BRAtS 2020 dataset, model SVM with Gaussian Kernel had the most remarkable accuracy of 89%	–
34.	(Ezhilarasi & Varalakshmi, 2018)	AlexNet is used as a base model along with region proposal network (RPN) by the faster R-CNN algorithm	Detection of brain tumor area is performed by predicting the type of tumor with a bounding box	The actual size of a tumor is not obtained
35.	(Hamghalam et al., 2020)	2D kernels from transformed 2D images are given into the classifier block for the prediction	The methodology presented in this research highlights discriminative pixels for the label prediction of center voxels by downscaling a 3D patch into a 2D image	Pixel-wise methods have limitations in inference time

(*Continued*)

Table 5. (*Continued*)

S. No.	Journal/paper year	Methodology	Advantages	Disadvantages
36.	(Chandra & Bajpai, 2020)	Super-diffusive model is used	Dependency on the mesh has been eliminated by using a mesh-free approach. The fractional partial differential equation is provided in the current publication	Preprocessing phase has not been employed in the proposed work
37.	(Shetty et al., 2022)	The capsNet-based model is used	The suggested approach was evaluated using BraTS18 data, which included two sets of data: HGG and LGG The model is compared to the U-Net model and uses dice coefficient, sensitivity, and specificity metrics	The dataset contains only HGG and LGG tumor images
38.	(Aswathy & Abraham, 2022)	BADF filter	The research mainly focuses on preprocessing astrocytoma images. This research project uses several filtering methods to increase image quality while reducing unneeded noise. In this work, the performance of BADF is assessed using several image filtering methods, including BF, CT, and AHE This suggested effort aims to choose the best noise-reduction filtering techniques	They are not focused on other steps like augmentation, detection, classification, etc.
40.	(Aswathy et al., 2019)	The generated brain MRI picture identifies and segments tumors using the support vector machine method	Extraction of texture features has shown to be quite helpful in identifying the segments. We use a wrapper-based evolutionary algorithm for the random search strategy in our suggested system to find the optimal components and SVM as the classifier	Challenging and time-consuming model

Table 6. Review from 2010 to 2017

S. no.	Journal/paper year	Methodology	Advantages	Disadvantages
1.	(Islam & Zhang, 2017)	Deep CNN and SVM	Significantly improvement in multi-class classification	The gradient is vanishingly tiny and consequently prevents
2.	(Yang et al., 2015)	Discrete wavelet transform (DWT)	Instead of dimensionality reduction on SVM	Model fitting issues are not resolved
3.	(Demirhan et al., 2014)	Neural networks, a self-organizing map (SOM), and wavelets	Performance increases in WM, GM, CSF, and edema	It should be implemented on most updates
4.	(Aneja & Rawat, 2013)	Fuzzy clustering means algorithms	Reduce the noise from the training set and size clot	A minuscule percentage of misclassification error
5.	(Kumar et al., 2010)	K means, neural networks, and fuzzy logic	Improve noisy image low error rate	The highly reduced misclassification error rate
6.	(Sapra et al., 2013)	Modified image segmentation techniques were applied to MRI scan images, the probabilistic neural network model, which is based on learning vector quantization, Canny edge detection algorithm	The hybrid technique is precise, quick, and durable	Various datasets produce different classification accuracy outcomes
7.	(Kanade & Gumaste, 2015)	Spatial FCM and the Stationary wavelet transform are used for image de-noising	Several techniques for de-noising in the wavelet domain were presented with wavelet transformations. Wavelets performed better at removing noise from images since they had features like multiresolution	The stationary wavelet transform is an intrinsically redundant technique since each level's output includes the same number of samples as its input, resulting in an N-fold redundancy in the wavelet coefficients for the decomposition of N levels
8.	(Hunnur et al., 2017)	It is primarily based on thresholding, using morphological techniques, and removing the tumor area for additional study	The area of the tumor region is calculated, and with this, the stage of the tumor patient is detected	Image resizing is a big task; it works only for black-and-white images and fails to detect the type of tumor
9.	(Hiran & Doshi, 2013)		An ANN approach is used to detect brain tumor which detects tumors by darkening the tumor portion	Since ANN is used, a large dataset will lead to complex computations that will consume more time
10.	(Bindu et al., 2022)	A pre-prepared VGG-16 convolutional model	The suggested CNN model comprises convolution, pooling, flattening, complete connection, and output layer. Based on dataset splitting, the performance is assessed. For a 70:30 splitting ratio, we achieve 78.98% accuracy, and for an 80:20 splitting ratio, we achieve 82.87% accuracy	A tiny dataset is used
11.	(Abhilasha et al., 2022)	Used an AlexNet-based architecture	We describe an AlexNet-based architecture that can classify images of meningiomas, gliomas, and pituitary tumors with an accuracy of 96.38% on the testing dataset and that can be trained in less than an hour	The model only functions with 2D images

7. Conclusion

Appropriate segmentation of MR images is crucial for improved diagnosis and therapy in patients with brain tumors. Accurate diagnosis, planning, and treatment require information from multiple slices. With the abundance of information available, computer processing is necessary for decision-making. Researchers prioritize improving the info obtained from collected slice images and optimizing the segmentation process over computation speed. This publication highlights substantial recent research efforts in brain tumor identification and segmentation. Automation of brain tumor identification and segmentation from brain MR images is a highly active area of research. Significant efforts have been made over many years, as evidenced in our literature review. However, few medical community has accepted an automated procedure.

In this publication, we tried to discuss a few of the substantial recent research efforts on brain tumor identification and segmentation. Automating brain tumor identification and segmentation from brain MR images is one of the most active study topics. Our literature examination shows significant research has been done in this area for many years. However, the medical community currently approves no automated procedure (Al-Tamimi & Sulong, 2014).

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

References

Abhilasha, K., Swati, S., & Kumar, M. (2022). Brain tumor classification using modified AlexNet network. In *Advances in Distributed Computing and Machine Learning: Proceedings of ICADCML 2022*, *427*, 425–433. https://doi.org/10.1007/978-981-19-1018-0_36

Al-Massri, R., Al-Astel, Y., Ziadia, H., Mousa, D. K., & Abu-Naser, S. S. (2018). Classification prediction of SBRCTs cancers using artificial neural network. *International Journal of Academic Engineering Research*, *2*(11), 1–7. http://ijeais.org/wp-content/uploads/2018/11/IJAER181101.pdf

Al-Mubayyed, O. M., Abu-Nasser, B. S., & Abu-Naser, S. S. (2019). Predicting overall car performance using artificial neural network. *International Journal of Academic and Applied Research*, *3*(1), 1–5. http://ijeais.org/wp-content/uploads/2019/01/IJAAR190101.pdf

Al-Tamimi, M. S. H., & Sulong, G. (2014). Tumor brain detection through MR images: A review of literature. *Journal of Theoretical & Applied Information Technology*, *62*(2), 387–403. http://www.jatit.org/volumes/Vol62No2/11Vol62No2.pdf

Amin, J., Sharif, M., Haldorai, A., Yasmin, M., & Nayak, R. S. (2021). Brain tumor detection and classification using machine learning: A comprehensive survey. *Complex & Intelligent Systems*, *8*(4), 3161–3183. https://doi.org/10.1007/s40747-021-00563-y

Amin, J., Sharif, M., Yasmin, M., & Fernandes, S. L. (2020). A distinctive approach in brain tumor detection and classification using M.R.I. *Pattern Recognition Letters*, *139*, 118–127. https://doi.org/10.1016/j.patrec.2017.10.036

Anand, V. K., Grampurohit, S., Aurangabadkar, P., Kori, A., Khened, M., Bhat, R. S., & Krishnamurthi, G. (2021). Brain tumor segmentation and survival prediction using automatic hard mining in 3D CNN architecture. In *Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries: 6th International Workshop*, 310–319. https://doi.org/10.1007/978-3-030-72087-2_27

Anaraki, A. K., Ayati, M., & Kazemi, F. (2019). Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms. *Biocybernetics and Biomedical Engineering*, *39*(1), 63–74. https://doi.org/10.1016/j.bbe.2018.10.004

Aneja, D., & Rawat, T. K. (2013). Fuzzy clustering algorithms for effective medical image segmentation. *International Journal of Intelligent Systems and Applications*, *5*(11), 55–61. https://doi.org/10.5815/ijisa.2013.11.06

Asodekar, B. H., & Gore, P. (2019). Brain tumor classification using shape analysis of M.R.I. images. In *Proceedings of International Conference on Communication and Information Processing*. https://doi.org/10.2139/ssrn.3425335

Aswathy, S. U., & Abraham, A. (2022). Preprocessing approach using BADF filter in MRI images for brain tumor detection. In *International Conference on Intelligent and Fuzzy Systems*, 558–567. https://doi.org/10.1007/978-3-031-09176-6_64

Aswathy, S. U., Glan Devadhas, G., & Kumar, S. S. (2019). Brain tumor detection and segmentation using a wrapper based genetic algorithm for optimized feature set. *Cluster Computing*, *22*, 13369–13380. https://doi.org/10.1007/s10586-018-1914-8

Badža, M. M., & Barjaktarović, M. Č. (2020). Classification of brain tumors from M.R.I. images using a convolutional neural network. *Applied Sciences*, *10*(6), 1999. https://doi.org/10.3390/app10061999

Bakas, S. (2020). Brats MICCAI brain tumor dataset. *IEEE DataPort*, *1*, 65–75. https://doi.org/10.21227/hdtd-5j88

Barhoom, A. M., Khalil, A. J., Abu-Nasser, B. S., Musleh, M. M., & Naser, S. S. A. (2019). Predicting Titanic survivors using artificial neural network. *International Journal of Academic Engineering Research*, *3*(9), 8–12. http://ijeais.org/wp-content/uploads/2019/09/IJAER190902.pdf

Bauer, S., Nolte, L. P., & Reyes, M. (2011). Fully automatic segmentation of brain tumor images using support vector machine classification in combination with hierarchical conditional random field regularization. In *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2011: 14th International Conference*, 354–361. https://doi.org/10.1007/978-3-642-23626-6_44

Bauer, S., Wiest, R., Nolte, L. P., & Reyes, M. (2013). A survey of MRI-based medical image analysis for brain tumor studies. *Physics in Medicine & Biology*, *58*(13), R97. https://doi.org/10.1088/0031-9155/58/13/R97

Bhanothu, Y., Kamalakannan, A., & Rajamanickam, G. (2020). Detection and classification of brain tumor in MRI images using deep convolutional network. In *6th International Conference on Advanced Computing and Communication Systems*, 248–252. https://doi.org/10.1109/ICACCS48705.2020.9074375

Bindu, J. H., Nikhil, K., Rao, K. R., Viswas, Y. D. S., & Charan, P. S. (2022). Computer aided diagnosis for brain tumor detection using VGG-16 and CNN models. *Gradiva Review Journal*, *8*(7), 197–202. https://doi.org/10.37897.GRJ.2021.V8I7.22.50018

Buckner, J. C., Brown, P. D., O'Neill, B. P., Meyer, F. B., Wetmore, C. J., & Uhm, J. H. (2007). Central nervous system tumors. *Mayo Clinic Proceedings*, *82*(10), 1271–1286. https://doi.org/10.4065/82.10.1271

Byale, H., Lingaraju, G. M., & Sivasubramanian, S. (2018). Automatic segmentation and classification of brain tumor using machine learning techniques. *International Journal of Applied Engineering Research*, *13*(14), 11686–11692. https://www.ripublication.com/ijaer18/ijaerv13n14_49.pdf

Chandra, S. K., & Bajpai, M. K. (2020). Brain tumor detection and segmentation using mesh-free super-diffusive model. *Multimedia Tools and Applications*, *79*(3–4), 2653–2670. https://doi.org/10.1007/s11042-019-08374-7

Chatterjee, S., Nizamani, F. A., Nürnberger, A., & Speck, O. (2022). Classification of brain tumours in MR images using deep spatiospatial models. *Scientific Reports*, *12*(1), 1505. https://doi.org/10.1038/s41598-022-05572-6

Cheng, J., Yang, W., Huang, M., Huang, W., Jiang, J., Zhou, Y., . . . , & Chen, W. (2016). Retrieval of brain tumors by adaptive spatial pooling and fisher vector representation. *PloS one*, *11*(6), e0157112. https://doi.org/10.1371/journal.pone.0157112

Clark, K., Vendt, B., Smith, K., Freymann, J., Kirby, J., Koppel, P., . . . , & Prior, F. (2013). The Cancer Imaging Archive (TCIA): Maintaining and operating a public information repository. *Journal of Digital Imaging*, *26*, 1045–1057. https://doi.org/10.1007/s10278-013-9622-7

Deepak, S., & Ameer, P. M. (2019). Brain tumor classification using deep CNN features via transfer learning. *Computers in Biology and Medicine*, *111*, 103345. https://doi.org/10.1016/j.compbiomed.2019.103345

Demirhan, A., Törü, M., & Güler, I. (2014). Segmentation of tumor and edema along with healthy tissues of brain using wavelets and neural networks. *IEEE Journal of Biomedical and Health Informatics*, *19*(4), 1451–1458. https://doi.org/10.1109/JBHI.2014.2360515

Deng, W., Xiao, W., Deng, H., & Liu, J. (2010). MRI brain tumor segmentation with region growing method based on the gradients and variances along and inside of the boundary curve. In *3rd International Conference on Biomedical Engineering and Informatics*, *1*, 393–396. https://doi.org/10.1109/BMEI.2010.5639536

Dheir, I. M., Mettleq, A. S. A., Elsharif, A. A., & Abu-Naser, S. S. (2019). Classifying nuts types using convolutional neural network. *International Journal of Academic Information Systems Research*, *3*(12), 12–18. http://ijeais.org/wp-content/uploads/2019/12/IJAISR191203.pdf

Dora, L., Agrawal, S., Panda, R., & Abraham, A. (2018). Nested cross-validation based adaptive sparse representation algorithm and its application to pathological brain classification. *Expert Systems with Applications*, *114*, 313–321. https://doi.org/10.1016/j.eswa.2018.07.039

Dvořák, P., & Menze, B. (2016). Local structure prediction with convolutional neural networks for multimodal brain tumor segmentation. *Medical Computer Vision: Algorithms for Big Data*, *9601*, 59–71. https://doi.org/10.1007/978-3-319-42016-5_6

El Kader Isselmou, A., Xu, G., Zhang, S., Saminu, S., & Javaid, I. (2019). Deep learning algorithm for brain tumor detection and analysis using MR brain images. In *Proceedings of the International Conference on Intelligent Medicine and Health*, 28–32. https://doi.org/10.1145/3348416.3348421

El-Melegy, M. T., & El-Magd, K. M. A. (2019). A multiple classifiers system for automatic multimodal brain tumor segmentation. In *15th International Computer Engineering Conference*, 110–114. https://doi.org/10.1109/ICENCO48310.2019.9027389

Ezhilarasi, R., & Varalakshmi, P. (2018). Tumor detection in the brain using faster R-CNN. In *2nd International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC) I-SMAC (IoT in Social, Mobile, Analytics and Cloud)*, 388–392. https://doi.org/10.1109/I-SMAC.2018.8653705

Geremia, E., Menze, B. H., & Ayache, N. (2012). Spatial decision forests for glioma segmentation in multi-channel M.R. images. In *Proceedings of MICCAI-BRATS*, *34*, 14–18. https://www-sop.inria.fr/asclepios/Publications/Ezequiel.Geremia/Geremia-BRATS-2012.pdf

Ghosal, P., Nandanwar, L., Kanchan, S., Bhadra, A., Chakraborty, J., & Nandi, D. (2019). Brain tumor classification using ResNet-101 based squeeze and excitation deep neural network. In *Second International Conference on Advanced Computational and Communication Paradigms*. https://doi.org/10.1109/ICACCP.2019.8882973

Gillies, R. J., Kinahan, P. E., & Hricak, H. (2016). Radiomics: Images are more than pictures, they are data. *Radiology*, *278*(2), 563–577. https://doi.org/10.1148/radiol.2015151169

Gooya, A., Pohl, K. M., Bilello, M., Cirillo, L., Biros, G., Melhem, E. R., & Davatzikos, C. (2012). GLISTR: Glioma image segmentation and registration. *IEEE Transactions on Medical Imaging*, *31*(10), 1941–1954. https://doi.org/10.1109/TMI.2012.2210558

Grampurohit, S., Shalavadi, V., Dhotargavi, V. R., Kudari, M., & Jolad, S. (2020). Brain tumor detection using deep learning models. In *IEEE India Council International Subsections Conference*, 129–134. https://doi.org/10.1109/INDISCON50162.2020.00037

Hamghalam, M., Lei, B., & Wang, T. (2020). Convolutional 3D to 2D patch conversion for pixel-wise glioma segmentation in MRI scans. In *BrainLes 2019: Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries*, 1199. https://doi.org/10.1007/978-3-030-46640-4_1

Havaei, M., Davy, A., Warde-Farley, D., Biard, A., Courville, A., Bengio, Y., . . . & Larochelle, H. (2017). Brain tumor segmentation with deep neural networks. *Medical Image Analysis*, *35*, 18–31. https://doi.org/10.1016/j.media.2016.05.004

Hiran, K. K., & Doshi, R. (2013). An artificial neural network approach for brain tumor detection using digital image segmentation. *Brain*, *2*(5), 227–231. https://api.semanticscholar.org/CorpusID:212484451

Hu, A., & Razmjooy, N. (2021). Brain tumor diagnosis based on metaheuristics and deep learning. *International Journal of Imaging Systems and Technology*, *31*(2), 657–669. https://doi.org/10.1002/ima.22495

Hunnur, S. S., Raut, A., & Kulkarni, S. (2017). Implementation of image processing for detection of brain tumors. In *International Conference on Computing Methodologies and Communication*, 717–722. https://doi.org/10.1109/ICCMC.2017.8282559

Imperial College London. (n.d.). *IXI dataset*. Retrieved from: http://brain-development.org/ixi-dataset/

Irmak, E. (2021). Multi-classification of brain tumor MRI images using deep convolutional neural network with fully optimized framework. *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, *45*(3), 1015–1036. https://doi.org/10.1007/s40998-021-00426-9

Islam, J., & Zhang, Y. (2017). A novel deep learning based multi-class classification method for Alzheimer's disease detection using brain MRI data. In *Brain Informatics: International Conference*, 213–222. https://doi.org/10.1007/978-3-319-70772-3_20

Jatin, G. (2022). Brain tumor image processing using fine-tuned resnet-101 classification model. *International Journal on Future Revolution in Computer Science & Communication Engineering*, *8*(1), 40–47. https://doi.org/10.17762/ijfrcsce.v8i1.2089

Jayadevappa, D., Kumar, S. S., & Murty, D. S. (2009). A hybrid segmentation model based on watershed and gradient vector flow for the detection of brain tumor. *International Journal of Signal Processing, Image Processing and Pattern Recognition*, *2*(3), 29–42. https://api.semanticscholar.org/CorpusID:17854268

Jiang, Y., Wu, D., Deng, Z., Qian, P., Wang, J., Wang, G., . . . , & Wang, S. (2017). Seizure classification from E.E.G. signals using transfer learning, semi-supervised learning and TSK fuzzy system. *IEEE Transactions on Neural Systems and*

Rehabilitation Engineering, *25*(12), 2270–2284. https://doi.org/10.1109/TNSRE.2017.2748388

Jiang, Y., Zhao, K., Xia, K., Xue, J., Zhou, L., Ding, Y., & Qian, P. (2019). A novel distributed multitask fuzzy clustering algorithm for automatic MR brain image segmentation. *Journal of Medical Systems*, *43*, 1–9. https://doi.org/10.1007/s10916-019-1245-1

Johnson, K. A. (2022). *Basic proton MR imaging*. Harvard Medical School. Retrieved from: http://www.med.harvard.edu/aanlib/basicsmr.html

Kanade, P. B., & Gumaste, P. P. (2015). Brain tumor detection using MRI images. *Brain*, *3*(2), 146–150. https://doi.org/10.17148/IJIREEICE.2015.3231

Khotanlou, H., Colliot, O., Atif, J., & Bloch, I. (2009). 3D brain tumor segmentation in MRI using fuzzy classification, symmetry analysis and spatially constrained deformable models. *Fuzzy Sets and Systems*, *160*(10), 1457–1473. https://doi.org/10.1016/j.fss.2008.11.016

Kleihues, P., Louis, D. N., Scheithauer, B. W., Rorke, L. B., Reifenberger, G., Burger, P. C., & Cavenee, W. K. (2002). The WHO classification of tumors of the nervous system. *Journal of Neuropathology & Experimental Neurology*, *61*(3), 215–225. https://doi.org/10.1093/jnen/61.3.215

Krishnakumar, S., & Manivannan, K. (2021). Effective segmentation and classification of brain tumor using rough K means algorithm and multi kernel SVM in MR images. *Journal of Ambient Intelligence and Humanized Computing*, *12*, 6751–6760. https://doi.org/10.1007/s12652-020-02300-8

Kumar, S., Dhir, R., & Chaurasia, N. (2022). Brain tumor detection analysis using CNN: A review. In *International Conference on Artificial Intelligence and Smart Systems*, 1061–1067. https://doi.org/10.1109/ICAIS50930.2021.9395920

Kumar, S., & Mankame, D. P. (2020). Optimization driven deep Convolution Neural Network for brain tumor classification. *Biocybernetics and Biomedical Engineering*, *40*(3), 1190–1204. https://doi.org/10.1016/j.bbe.2020.05.009

Kumar, S. S., Moorthi, M., Madhu, M., & Amutha, R. (2010). An improved method of segmentation using fuzzy-neuro logic. In *Second International Conference on Computer Research and Development*, 671–675. https://doi.org/10.1109/ICCRD.2010.155

Kwon, D., Shinohara, R. T., Akbari, H., & Davatzikos, C. (2014). Combining generative models for multifocal glioma segmentation and registration. In *Medical Image Computing and Computer-Assisted Intervention–MICCAI: 17th International Conference*, 763–770. https://doi.org/10.1007/978-3-319-10404-1_95

Landis, S. H., Murray, T., Bolden, S., & Wingo, P. A. (1998). Cancer statistics, 1998. *CA: A Cancer Journal for Clinicians*, *48*(1), 6–29. https://doi.org/10.3322/canjclin.48.1.6

Le Folgoc, L., Nori, A. V., Ancha, S., & Criminisi, A. (2016). Lifted auto-context forests for brain tumour segmentation. In *BrainLes 2016: Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries: Second International Workshop*, *10154*, 171–118. https://doi.org/10.1007/978-3-319-55524-9_17

LeCun, Y., & Bengio, Y. (1995). Convolutional networks for images, speech, and time series. In. M. A. Arbib (Ed.), *The handbook of brain theory and neural networks* (pp. 276–279). MIT Press Cambridge. MA, USA.

Lei, X., Yu, X., Chi, J., Wang, Y., Zhang, J., & Wu, C. (2021). Brain tumor segmentation in MR images using a sparse constrained level set algorithm. *Expert Systems with Applications*, *168*, 114262. https://doi.org/10.1016/j.eswa.2020.114262

Louis, D. N., Ohgaki, H., Wiestler, O. D., Cavenee, W. K., Burger, P. C., Jouvet, A., . . . , & Kleihues, P. (2007). The 2007 WHO classification of tumours of the central nervous system. *Acta Neuropathologica*, *114*, 97–109. https://doi.org/10.1007/s00401-007-0243-4

Maram, B., & Rana, P. (2021). Brain tumour detection on brats 2020 using u-net. In *9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)*, 1–5. https://doi.org/10.1109/ICRITO51393.2021.9596530

Methil, A. S. (2021). Brain tumor detection using deep learning and image processing. In *International Conference on Artificial Intelligence and Smart Systems*, 100–108. https://doi.org/10.1109/ICAIS50930.2021.9395823

Miglani, A., Madan, H., Kumar, S., & Kumar, S. (2021). A literature review on brain tumor detection and segmentation. In *5th International Conference on Intelligent Computing and Control Systems*, 1513–1519. https://doi.org/10.1109/ICICCS51141.2021.9432342

Naseer, A., Yasir, T., Azhar, A., Shakeel, T., & Zafar, K. (2021). Computer-aided brain tumor diagnosis: Performance evaluation of deep learner CNN using augmented brain MRI. *International Journal of Biomedical Imaging*, *2021*, 5513500. https://doi.org/10.1155/2021/5513500

Noback, C. R., Strominger, N. L., Demarest, R. J., & Ruggiero, D. A. (2005). *The human nervous system: Structure and function*. Germany: Springer Nature.

Paszkiel, S. (2020). Data acquisition methods for human brain activity. In S. Paszkiel (Ed.), *Analysis and classification of EEG signals for brain–computer interfaces* (pp. 3–9). Switzerland AG: Springer Nature. https://doi.org/10.1007/978-3-030-30581-9_2

Pereira, S., Pinto, A., Alves, V., & Silva, C. A. (2016). Deep convolutional neural networks for the segmentation of gliomas in multi-sequence MRI. In *Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries*, 131–143. https://doi.org/10.1007/978-3-319-30858-6_12

Pitchai, R., Supraja, P., Victoria, A. H., & Madhavi, M. J. N. P. L. (2021). Brain tumor segmentation using deep learning and fuzzy K-means clustering for magnetic resonance images. *Neural Processing Letters*, *53*, 2519–2532. https://doi.org/10.1007/s11063-020-10326-4

Prastawa, M., Bullitt, E., Ho, S., & Gerig, G. (2004). A brain tumor segmentation framework based on outlier detection. *Medical Image Analysis*, *8*(3), 275–283. https://doi.org/10.1016/j.media.2004.06.007

Qian, P., Xu, K., Wang, T., Zheng, Q., Yang, H., Baydoun, A., . . . & Muzic, R. F. (2020). Estimating CT from MR abdominal images using novel generative adversarial networks. *Journal of Grid Computing*, *18*, 211–226. https://doi.org/10.1007/s10723-020-09513-3

Radiopaedia.org. (2021). *T2 weighted image*. Retrieved from: https://radiopaedia.org/articles/6345

Radiopaedia.org. (2023a). *Fluid attenuated inversion recovery*. Retrieved from: https://radiopaedia.org/articles/21760

Radiopaedia.org. (2023b). *Diffusion-weighted imaging in acute ischemic stroke*. Retrieved from: https://radiopaedia.org/articles/13401

Rajan, P. G., & Sundar, C. (2019). Brain tumor detection and segmentation by intensity adjustment. *Journal of Medical Systems*, *43*, 1–13. https://doi.org/10.1007/s10916-019-1368-4

Reyes, K. (2023). *What is deep learning and how does it works*. Retrieved from: https://www.simplilearn.com/tutorials/deep-learning-tutorial/what-is-deep-learning

Rizwan, M., Shabbir, A., Javed, A. R., Shabbir, M., Baker, T., & Obe, D. A. J. (2022). Brain tumor and glioma grade classification using Gaussian convolutional neural network. *IEEE Access*, *10*, 29731–29740. https://doi.org/10.1109/ACCESS.2022.3153108

Sahaai, M. B., Jothilakshmi, G. R., Ravikumar, D., Prasath, R., & Singh, S. (2022). ResNet-50 based deep neural network using transfer learning for brain tumor classification. *AIP Conference Proceedings*, *2463*(1), 020014. https://doi.org/10.1063/5.0082328

Saleh, A., Sukaik, R., & Abu-Naser, S. S. (2020). Brain tumor classification using deep learning. In *International Conference on Assistive and Rehabilitation Technologies*, 131–136. https://doi.org/10.1109/iCareTech49914.2020.00032

Sangeetha, R., Mohanarathinam, A., Aravindh, G., Jayachitra, S., & Bhuvaneswari, M. (2020). Automatic detection of brain tumor using deep learning algorithms. In *4th International Conference on Electronics, Communication and Aerospace Technology*, 1–4. https://doi.org/10.1109/ICECA49313.2020.9297536

Sapra, P., Singh, R., & Khurana, S. (2013). Brain tumor detection using neural network. *International Journal of Science and Modern Engineering*, *1*(9), 83–87. https://www.ijisme.org/portfolio-item/i0425081913/

Shah, H. A., Saeed, F., Yun, S., Park, J. H., Paul, A., & Kang, J. M. (2022). A robust approach for brain tumor detection in magnetic resonance images using finetuned EfficientNet. *IEEE Access*, *10*, 65426–65438. https://doi.org/10.1109/ACCESS.2022.3184113

Shahid, A., Khan, M. S., Habib, U., Mukhtar, S., Ahmed, A., & Shahid, S. (2022). Detection of brain tumour in 3D MRI. In *International Conference on IT and Industrial Technologies*, 1–7. https://doi.org/10.1109/ICIT56493.2022.9989020

Shakeel, P. M., Tobely, T. E. E., Al-Feel, H., Manogaran, G., & Baskar, S. (2019). Neural network based brain tumor detection using wireless infrared imaging sensor. *IEEE Access*, *7*, 5577–5588. https://doi.org/10.1109/ACCESS.2018.2883957

Shetty, J., Shetty, S., Shetty, V., & Rai, C. (2022). Brain tumor segmentation using capsule neural network. In *Recent Advances in Artificial Intelligence and Data Engineering: Select Proceedings of AIDE 2020*, 205–212. https://doi.org/10.1007/978-981-16-3342-3_17

Siar, M., & Teshnehlab, M. (2019). Brain tumor detection using deep neural network and machine learning algorithm. In *9th International Conference on Computer and Knowledge Engineering*, 363–368. https://doi.org/10.1109/ICCKE48569.2019.8964846

Stadlbauer, A., Moser, E., Gruber, S., Buslei, R., Nimsky, C., Fahlbusch, R., & Ganslandt, O. (2004). Improved delineation of brain tumors: An automated method for segmentation based on pathologic changes of 1H-MRSI metabolites in gliomas. *Neuroimage*, *23*(2), 454–461. https://doi.org/10.1016/j.neuroimage.2004.06.022

Suhara, S. F., & Mary, M. S. (2018). Fully connected pyramid pooling network (FCPPN)–A method for brain tumor segmentation. *International Journal of Engineering and Advanced Technology*, *9*(1), 7036–7041. http://doi.org/10.35940/ijeat.A1658.109119

Tang, M. Y., Chen, T. W., Zhang, X. M., & Huang, X. H. (2014). GRE T2-weighted MRI: Principles and clinical applications. *BioMed Research International*, *2014*, 312142. https://doi.org/10.1155/2014/312142

Varuna Shree, N., & Kumar, T. N. R. (2018). Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network. *Brain Informatics*, *5*(1), 23–30. https://doi.org/10.1007/s40708-017-0075-5

Wang, S., & Summers, R. M. (2012). Machine learning and radiology. *Medical Image Analysis*, *16*(5), 933–951. https://doi.org/10.1016/j.media.2012.02.005

Wu, W., Li, D., Du, J., Gao, X., Gu, W., Zhao, F., . . . , & Yan, H. (2020). An intelligent diagnosis method of brain MRI tumor segmentation using deep convolutional neural network and SVM algorithm. *Computational and Mathematical Methods in Medicine*, *2020*. https://doi.org/10.1155/2020/6789306

Xia, K., Zhong, X., Zhang, L., & Wang, J. (2019). Optimization of diagnosis and treatment of chronic diseases based on association analysis under the background of regional integration. *Journal of Medical Systems*, *43*, 1–8. https://doi.org/10.1007/s10916-019-1169-9

Yan, L. C., Yoshua, B., & Geoffrey, H. (2015). Deep learning. *Nature*, *521*(7553), 436–444.

Yang, G., Nawaz, T., Barrick, T. R., Howe, F. A., & Slabaugh, G. (2015). Discrete wavelet transform-based whole-spectral and subspectral analysis for improved brain tumor clustering using single voxel MR spectroscopy. *IEEE Transactions on Biomedical Engineering*, *62*(12), 2860–2866. https://doi.org/10.1109/TBME.2015.2448232

Zhang, Z., & Sejdić, E. (2019). Radiological images and machine learning: Trends, perspectives, and prospects. *Computers in Biology and Medicine*, *108*, 354–370. https://doi.org/10.1016/j.compbiomed.2019.02.017

Zikic, D., Ioannou, Y., Brown, M., & Criminisi, A. (2014). Segmentation of brain tumor tissues with convolutional neural networks. In *Proceedings MICCAI-BRATS 2014*, *36*, 36–39.

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