A Review on Artificial Intelligence Based Heuristic Models for Brain Tumor Image Classification and Segmentation

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Even with the tremendous advancements in medical technology, the most laborious and complex work that doctors still have to do is segment tumors. Radiologists most commonly employ magnetic resonance imaging (MRI) to examine interior human body parts without dissecting them, although manual inspection is time-consuming and wastes valuable work hours. Since it might lead to early diagnosis, effective automated sorting of brain cancers from MRI images is crucial, reduce errors in work hours, propagate automation in tumor removal, and aid in treatment decision-making. Computer-aided image analysis can also be a potential solution for early disease detection, such as cancer or tumors. This paper seeks to emphasize the strategies in light of these challenges. For physicians, identifying tumors in the brain is still a highly challenging and lengthy procedure. despite the tremendous advancements in medical technology. Early and comprehensive brain tumor detection may result in higher survival rates since it enables effective and efficient treatment. Enhanced efficiency and consistent precision could come from the computerized recognition and categorization of brain tumors. However, it is well recognized that the strategy and picture modality have an impact on the accuracy performance of automatic detection and classification techniques. The latest detection methods are reviewed in this work along with their benefits and drawbacks.

Povzetek: Za klasifikacijo in segmentacijo možganskih tumorjev iz MRI je narejen pregled AI-heurističnih pristopov (CNN, DL) z poudarkom na predobdelavi (izenačevanje histogramov), izbiri značilk in primerjavi metod; sintetizira ključne naborčke (BRATS, OASIS, TCIA, IBSR ...). Izpostavi prednosti/slabosti ter smeri nadaljnjega razvoja za zanesljivejšo avtomatizacijo.

1 Introduction

We still don't entirely grasp how the brain of human's functions, despite it having the most complicated organ. In the event that there is an anomaly, its effects are also unclear and vary from person to person. A tumor is the most hazardous of these abnormalities. There are two stages to a tumor: benign and malignant. Benign types are less dangerous since they are not invasive and, once eliminated from the body, do not constitute a threat; malignant types, on the other hand, are constantly returning and are thus categorized as cancerous. The only way to enhance a tumor patient's prognosis is to identify and classify the tumor in its early stages. For a while, manual examination was the accepted method for identifying tumors in magnetic resonance imaging. Many works regarding detection and classification have been proposed recently due to advancements in sensory and image processing technology. A variety of approaches, including picture categorization, equalization of histograms, choosing features, removal, categorization, and picture improvement. As the cancer cells proliferate, a lump of tissue called a tumor is created. Naturally, body cells divide and get substituted by fresh cells. The presence of malignant and other tumors considerably disrupts this stage.

Tumor cells proliferate and do not die like healthy cells do, even if the body does not need them. As more cells are added to the bulk throughout this phase, the cancer continues to spread. One term for a primary brain tumor that is rapidly spreading is "glioma." Glial tissue, from which gliomas grow, supports and nurtures the cells that carry messages from the brain to various body areas. Benign and malignant (cancerous) brain tumors are the two varieties. Body growths that are benign and incapable of spreading to neighbouring tissue have been identified as not malignant tumors. They are unlikely to return and can be totally removed. Excruciating agony, irreparable brain damage, and death are all possible outcomes of benign brain tumors. They don't spread to nearby tissue. There are no limits to malignant brain tumors. Their rapid development and ability to extend across the brain or spinal cord beyond their original location can strain the brain.

2 Brain tumor detection

According to the data, brain tumors account for the greatest fatality rate worldwide. Symptoms include mood swings, slurred speech, blood clots, weakness, uncontrolled walking, hormonal changes, and vision loss. The research claims that brain tumors are the world's greatest cause of death.

Hormonal fluctuations, blood clots, weakness, uncontrollably walking, slurred speech, loss of eyesight, and mood swings are some of the symptoms. The type of tumor is determined by its location, and an accurate diagnosis can preserve the patient's life [1]. Benign tumors are benign growths that do not have the ability to spread to nearby tissue and are not malignant. They can be eliminated entirely, and they are not likely to come back. Benign brain tumors can result in death, severe discomfort, and long-lasting brain damage, but they do not spread to nearby tissue. There are no clear boundaries for malignant brain tumors. They have the capacity to proliferate rapidly, raising intracranial pressure, and to disperse throughout the brain or spinal cord beyond their initial site. A malignant brain tumor seldom spreads to other parts of the brain. Technological advancements have the capacity to impact all facets of human existence. The medical industry is a prominent illustration of how technology has advanced human civilization.

Technology-assisted treatment of brain tumors, which are among the most prevalent and fatal diseases worldwide, is the main topic of this article. Every year, a significant number of people lose their lives to brain tumors. Over 700,000 Americans currently have primary brain tumors, according to the "brain tumor" website, and this number rises by an additional 85,000 every year. Both medication and artificial intelligence have been used to overcome this issue.

For the diagnosis of brain cancer, magnetic resonance imaging (MRI) is the most widely used method. In the processing of images and medical imaging, magnetic resonance imaging (MRI) is also commonly used for recognizing changes in different body parts. In order to identify present problems in the field and propose future directions, we conducted a thorough examination of prior attempts to apply different deep learning algorithms to MRI data. One of the subdivisions of deep learning that has shown exceptional performance in evaluating medical images is CNN. Consequently, our investigation focused on processing medical images, namely brain MRI data, and looked at a number of CNN configurations.

For children under 20, brain tumors rank as the following most frequent cause of cancer-related mortality and the fifth most common cause in those aged 20 to 39, according to statistics from the Central Brain Tumor Registry of the United States (CBTRUS). A primary brain tumor often requires a 60-year-old diagnosis. A brain or CNS tumor will also be diagnosed in roughly 3540 children under the age of 15 in 2020, according to the statistics [2] For humans, a brain tumor is a major therapy. A tumor is an abnormal brain cell development. Two kinds of tumors are distinguished. Malignant tumors are those that are cancerous, whereas benign tumors are those that are not. Inevitably, because of their quick growth, ability to spread. To greater cortical and lumbar regions, as well as the potential for death, malignant brain tumors are the main reason for concern. The prompt identification of a tumor is essential for its treatment; there are a number of methods for diagnosing this condition, but doctors first use imaging methods since they allow them to see the tumor immediately.

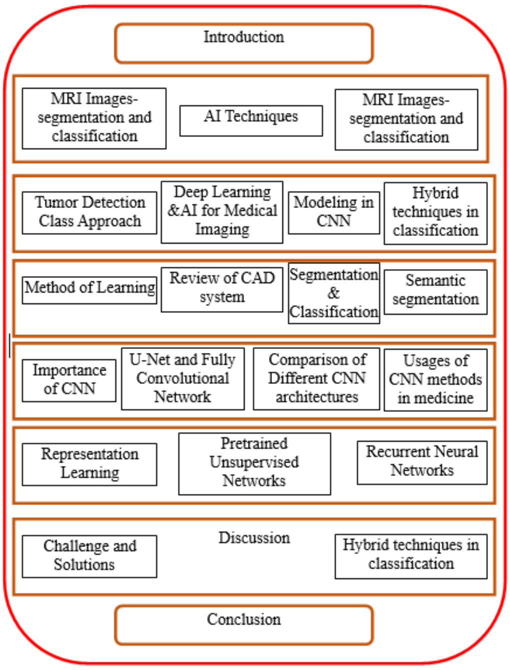

Figure 1: The structure of this survey

3 Techniques in brain tumor detection

We go over the subjects that are connected to the study's theme in this portion. The significance of segmentation and classification in medical pictures is examined first, in addition to the difficulty of identifying brain malignancies in MRI pictures.

Our second area of study is artificial intelligence, namely machine learning, deep learning, and neural networks. Third, we incorporate CNN for image processing and look at some applications of deep learning in medical imaging.

In image processing methods, picture segmentation and classification are used to divide the ROI. Image segmentation and classification are essential for comprehending, analysing, interpreting, and extracting characteristics from images. Medical image segmentation is a method for separating the image into distinct areas or parts or establishing the region of interest (ROI).

3.1 Segmentation and classification with MRI images

MRI Image Division and Classification When a brain tumor's precise location is unknown, it may be evacuated improperly or insufficiently, which encourages the tumor's growth and spread. The chance of dying rises under certain situations. This problem can be avoided or mitigated by using methods for analysing images. Techniques for processing MR scans might be entirely computerized, partially automated, or manual.
Completely automated or partially automated procedures are faster and more accurate than manual ones in medical image processing. Furthermore, because medical issues involve human life and expert opinions are crucial, further study is still needed to establish a completely automated and efficient classification. Researchers have proposed several methods to build these knowledge bases and so improve the performance of tumor detection systems.
In neurology, magnetic resonance imaging (MRI) is a commonly employed and flexible way of imaging the brain's minute traits and other cranial structures. MRI may indicate fundamental vascular problems alongside blood flow.

An MRI scan can also help and benefit other brain-related disorders like dementia [14], Parkinson's disease [13], and Alzheimer's disease [12]. MRI images were also used to examine the impact of COVID-19 on tissue in the brain in [15][16], along with numerous other disorders. Various datasets are offered for training and testing. Table 1[20] contains typical datasets for MR segmentation of images.

Table 1: MR image collections that are accessible

Ref. No	Dataset	Description	Features
[17]-[19]	BRATS	The Brain Tumor Segmentation Challenge (BRATS) uses data from 2012 to 2020 and is always focused on evaluating new and existing techniques for brain tumor segmentation in multimodal MR images.	In tandem with the MICCAI 2012 and 2013 conferences, fully convolutional neural networks (FCNN) and conditional random fields (CRF) are utilized in the segmentation of brain tumors.
[20]-[21]	OASIS	Over 2000 MR sessions are gathered from many active investigations through the WUSTL Knight ADRC and are included in an open access series of imaging studies.	Alzheimer's disease diagnostic.
[22]-[24]	TCIA	The public can obtain a large collection of cancer images from the Cancer Imaging Archive (TCIA).	Pancreatic cancer prediction and head and neck cancer prediction. Brain tumor segmentation.
[6],[25], [26]	IBSR	The brain dissection repository on the internet. Its objective is to promote the assessment and development of segmentation techniques.	MRI segmentation of images and skull scraping
[27]-[29]	Brain Web	It is a database of simulated brains.	CNN-based 3D MR image restoration, MRI noise reduction, and CNN-based brain volume and cerebrospinal fluid segmentation
[30]	NBIA	Access to picture archives is provided by the National Biomedical Imaging Archive, which contains in vivo images relevant to the biomedical research belonging, business, and university.	Network for Parametric Imaging
[31]-[32]	The Whole Brain Atlas	Anyone may view PET and MRI scans of both healthy and damaged brains on the Harvard Whole Brain Atlas, and this website has dozens of actual images of the brain.	CNN and serotonin neurons are used to extract features from brain pictures.
[7], [33]	ISLES	The MICCAI 2018 Ischemes Stroke Lesion Segmentation Challenge features a fresh dataset with 103 stroke patients that matches expert segmentations.	Segmenting stroke and brain lesions independently

This issue may be partially resolved by an automated model; for example, we can apply the object detection and abnormality approaches. The effectiveness of automated techniques is restricted to knowledge databases due to a lack of expertise. Numerous computerized techniques along with information bases have been developed by researchers to increase the efficacy of malignancy detection tools [25][26].

3.2 Deep learning approaches

Multi-level representation machine learning approaches have been shown via deep learning. It has several layers, each of which receives a representation from a previous level as input. Using this structure, it is possible to learn exceedingly complicated characteristics and inferences.

Due to its many uses in a variety of fields, including pattern identification, anomaly detection, object or image detection, and natural language processing, deep learning has been gaining a lot of attention lately. Deep learning may be very helpful for applications such as natural language processing, pattern identification, anomaly detection, and image detection. The three distinct subgroups of artificial intelligence (AI) are convolutional neural networks (CNNs), pre-trained unsupervised networks (PUNs), and recurrent/recursive neural networks (RNNs).

Learning deeply in the medical field provides physicians with the means to make better decisions and more accurate diagnoses and treatments.

3.3 Complexes of neurons

In order to find patterns in large amounts of data, neurons are sets of algorithms that mimic how the brain of humans works. Neural networks (NNs) and deep learning (DL) have outperformed conventional techniques in object recognition in recent years.
Given their powerful representational skills and

increasing prominence in modeling abstract notions, NNs may be able to acquire intricate hierarchical representations of images.

They are quite good at extrapolating data that has never been seen before. This characteristic enables them to identify a wide variety of items whose appearances also differ significantly [24] NNs provide neuroscientists a novel method for understanding complicated behaviors and varied brain activity in neural systems [33]. The ability to train neural networks end-to-end and their ability to powerfully generalize previously unseen data are two of its advantages.

3.4 Learning through machine learning

A logical extension of computer science and statistics is machine learning. Internal components of machine learning parameters are independently tuned to promote learning. To create feature extractors, machine learning techniques [64][65][66][67] require meticulous engineering and domain knowledge expertise: This led to the creation and introduction of a convolution neural network (CNN) by Yann LeCun [27][28] that is capable of learning to derive elements.

The domain is medical imaging has experienced a notable transformation due to the advancements in machine learning and soft computing techniques [44]. The selection of data attributes that machine learning techniques are used to affects how effective the techniques are.

Machine learning is clearly useful for extracting radiomic information from photos, as Lambin initially noted in [45]. They discussed the limitations of solid cancer, despite its enormous promise for medical imaging and feature extraction. Radiomics tackles this issue by extracting many image characteristics from radiography images; nevertheless, additional validation in multicentric settings and in the laboratory is still required. Typically, radiomic characteristics determine a single scalar value that represents the full three-dimensional (3D) tumor volume. An example of a useful classifier is a decision tree. Results that can be fed into the classifier are linked to specific qualities. ML pinpoints the key elements that result in the greatest level of prediction ability.

4 Literature survey

A summary of recent medical studies on identifying tumors is given in this section. Medical image processing includes the classification of images for the purpose of identifying and identifying abnormalities based on magnetic resonance imaging. [3] presents the key characteristics of the various forms of brain tumors as well as the segmentation and classification methods that are useful for detecting a variety of brain diseases. For MR images, this study presents the most relevant guidelines, practices, constraints, strategies, and preferences. The reviews in [51] provides the creation of a computerized method for the detection of brain tumors using MRI utilizing artificial neural networks; feature extraction is advised for the image segmentation methods gathered for this study. The recommended approach produced the greatest results (99% accuracy and 97.9% sensitivity) in tests. Article [52] suggests an artificial intelligence learning-based approach to identifying tumors in the brain. To extract attributes based on texture, the grey level co-occurrence matrix (GLCM) is utilized. The categorization technique considers 212 samples of brain MR images and uses the Naive Bayes machine learning method with opinion. In [53], the tumor identification potential of the CNN-based planned division method is explored. To detect cancers from MRI images, classification via SVM is done by employing the MATLAB software.

A summary of tumor identification methods and procedures based on findings from medical imaging is available in [54]. Using BraTS 2015, an entirely computerized approach for brain tumor identification and localization with U-Net-based deep convolution networks has been presented in [55]. In this study, the brain sectioning of tumors model that does not require contact between people is presented.

Accurate segmentation was achieved in [56] by combining deep learning and manually created features for photo segmentation using the grab-cut technique. In [57], an automated technique It is designed to extract and classify tumors from MRIs using features selection and marker-based watershed segmentation. The most challenging example of brain tumor was diagnosed by the investigators using deep CNN in Ref. [9]. Their database has 1258 MRI pictures from 60 different patients that were produced with MATLAB software. 96% of the study's data were credible.

Cognitive imaging techniques provide plenty of ideas for improving picture data exchange across different systems [58]. Radiologists may now more accurately identify benign and dangerous malignancies from MRI pictures of breast lesions thanks to artificial intelligence [59]. More accurate patient identification by radiologists thanks to AI may enhance the prognosis and treatment plan for those patients.

A high-performance method was created in [60] to identify and describe the existence of a disc rip on a knee MRI scan. The literature on radiomics, or artificial intelligence (AI), and all types of medical imaging modalities for the oncological and non-oncological uses of conventional medicine is summarized in [61].

A broad overview of MRI image processing and analysis using deep learning is provided in [62]. In [63], a deep learning algorithm is combined with an end-to-end training methodology to create a deep learning method that can accurately detect breast cancer from screening mammograms. The key ideas of deep learning for the interpretation of medical images are explained in [39].

Convolutional neural networks' possible direct use to brain tumor tissue segmentation was examined by Darko Zikic et al. [26]. The issue is that for every point that needed categorization, the network received multi-channel intensity data from a tiny region. To take scanner variations into consideration, the input data was pre-processed using only standard intensity. The CNN output did not undergo any post-processing. In their survey [27], Jose Bernal et al. looked at CNN techniques, concentrating on MRI image interpretation structures, pre-processing, data preparation, and post-processing phases. They investigated novel approaches and the creation of multiple CNN design.

In [8], Amin Kabir et al. developed a methodology based on the integration of CNN with biological algorithms. They suggested employing flagging as a team approach to quietly categorize distinct stages of gliomas based on MRI scans in order to decrease the variety of prediction error. Jin Liu and Min Li [1] introduced the idea of dividing brain tumors using strategies and provided preprocessing techniques for applications such object recognition, registration, and MRI-based sectioning of brain tumors. False positives are successfully eliminated by the 3D completely linked dependent random field employed in [7]. They also proposed a 3D CNN architecture for automated lesion segmentation.

In order to encourage deep neural networks to acquire stronger multifaceted features, the dual-force training technique was suggested in [28]. Roughly totally convolutional network with an adjustable input size that enables efficient inference and learning while producing an output of a similar size is the central idea of [29]. To segment and evaluate images slice per slice, Havaei et al. [4], for instance proposed using FCNN. In an effort to solve the issue of class imbalance, a multiple stages training program was also suggested. Multimodal brain tumor image segmentation was demonstrated by Menz et al. [19]. This approach may be classified as discriminative or generative. For 3D-based deep learning components, Fritscher et al. [12] introduced a CNN with three convolutional passes. displayed a multi-modal picture DCNN. [13]. Three different designs were proposed, each with a different patch (input) size" Using a patch technique for brain tumor segmentation also shown that the parabolic determine and patch measurement had an impact on the outcomes.

With two adjustments, this model's efficiency is similar to that of the U-Net CNN the field of architecture: (1) From one network stage to the next, feature mappings are assigned via element-wise summation and (2) it combines multiple segmentation maps made at different sizes [23]. Based on medical imaging data, the Hand and brain MRIs are subjected to a CNN-based method using multifaceted filters in [34]. Along with two changes to an existing CNN architecture, strategies to overcome the aforementioned issues are also examined. This model might be the best in both ischemic stroke lesion segmentation (ISLES) and BraTS 2015.

Since segmentation as well as the hardest and most crucial are classification. image processing subjects for brain tumor research, they are the focus of this survey. The technique of breaking up a single image into multiple parts is called segmentation. Segmentation can also be carried out based on functional regions, tissue kinds, etc. Tumor segmentation is accessible in three different types: completely automatic, semi-automated, and manual. In a completely automatic technique, all work is done by computers; often, this approach is coupled with artificial intelligence, which makes use of CAD systems and machine learning algorithms. Medical picture analysis and recognition are automated by machine learning. Since clustering employs group data that meet certain similarity requirements, it is the most popular unsupervised segmentation technique for brain tumors. MRI picture segmentation requires automated methods since MRI scans generate a lot of data. Before being segmented, images need to be pre-processed for specific segmentation goals. Preprocessing includes a number of procedures, such as intensity, normalization, de-noising, and skull-stripping.

Often, segmentation is done by hand, which limits the ability to undertake an objective qualitative evaluation and is time-consuming and difficult for radiologists. The subjective opinions and experiences of the judges constitute the foundation of the manual sorting process. It may therefore contain mistakes. In practice, therefore, it is very desirable to have fully automated and accurate brain tumor segmentation systems. For medical imaging to monitor the expansion or shrinkage of tumors in patients during treatment, segmentation is crucial.

Additionally, during surgery and tumor volume assessments, it can be used to identify areas that contain tumors. Many of the methods employed for neurological tumor categorization, including support vector machines (SVM), fuzzy c-means (FCM), k-means, Markov random fields (MRF), Bayes, and artificial neural networks (ANN), are based on classification or clustering techniques.

Computational and discriminatory models are the two types of brain tumor segmentation models. The foundation of predictive models is domain-specific information regarding the appearance of tumorous and healthy tissues. Generative models comprise conditional random fields and Markov random fields (MRF).

CNN is one of the neural networks that may directly learn the link between segmentation labels and picture intensities, obviating the necessity for domain expertise [19]. In a pattern classification setting, these models are capable of handling the segmentation problem. Because deep convolutional neural networks (DCNNs) can learn information on their own and give complicated function mapping, they are used in complex image processing. This method comes in two varieties: patch-based and end-to-end. The path-based technique feeds the network patches, which are usually odd and fixed size, with the class of the central pixel as the output.

One type of conventional neural network is the multilayer perceptron (MLP). Using a perceptron for each input is one of MLP's drawbacks, which leaves it uncontrollable for images with a lot of weight. Another problem is the discrepancy between MLP's response to input (images) and its modified form. Since spatial information is lost when a picture is flattened into one, MLPs are not a viable choice for image processing. Convolutional neural networks are among the most successful deep learning techniques for image analysis to date, and they have significantly improved the field of image processing.

When it comes to solving difficult machine learning problems, (CNNs/ConvNets) have advanced significantly. One of the main classes of neural networks is CNN. CNN image classifiers look at incoming photos and divide them into categories like cats and dogs. CNN is tasked with reducing the size of a picture to facilitate processing without compromising any of the crisp features required for a precise prediction. CNN does a great job of analyzing images and recognizing features. CNN is necessary for many deep neural network applications. As demonstrated by their recent impressive achievement of visual analysis tasks, including recognizing and segmenting of pictures, CNNs may be able to automatically identify the most valuable characteristics in images. These neural layers—the kernel, pooling, fully connected, and Soft-Max functions—process every data input. A CNN stream in its entirety that analyses an input image and classifies items according to values is displayed in Fig. 1. CNN is made up of several layers that alter their input slightly using convolution filters. The three core layers of a convolutional network are convolutional (sets of learnable filters), pooling (used to minimize image size and prevent overfitting), and fully connected (used to merge spatial and channel data). Fig. 1 displays the CNN layers. The majority of these networks' layers make use of convolution operators. CNNs have been employed in recent years to segment Deep brain anatomical characteristics, cerebral microbleeds, and lesions associated with MS. Since thousands of MRI pictures of various sorts and quality are utilized for diagnosis, CNN is employed to classify images of brain tumors because it can reduce high computing expenses.

CNN has the capacity to further reduce the dimensions and automatically extract features. CNN has done a good job at utilizing massive brain structures for medical picture analysis. Statistical algorithms, also known as convolutional networks, have swiftly emerged as the preferred technique for interpreting medical images.

Table 2: CNN Modalities analysis

Scheme	Dataset	Ways of Training and Testing	Achievement
Trust CNN.	2015 BRATS and 2015 ISLES	Two-way	Parallel convolutional pathways provide an effective multi-scale processing solution for huge image contexts.
	2017 BRATS and 2015 BRATS	Two-force	Excellent quality attributes with multiple levels were learned via dual force training.
	2013 BRATS and 2015 BRATS	Using patches	enabled more sophisticated CNN-based segmentation methods for brain MRI images by utilizing 3x3 kernels.
Rely on DCNN	ImageNet LSVRC 2010	Using patches	obtained highest-1 and highest-5 failure rates of 37.5% and 17%, respectively.
	BRATS 2013	T1,T1c,T2 and FLAIR images	Combining Conditional Random Fields with FCN to segment brain tumors.
	BRATS 2013	T1,T1c,T2 and FLAIR images	As demonstrated at MICCAI 2013, a novel CNN design increased speed and accuracy.
Rely on FCN	BRATS 2013 & 2016	T1,T1c,T2 and FLAIR images	Combining Conditional Random Fields with FCN to Segment Brain Tumors
	BRATS 2013	End to End	Enhance FCN and brain tumor segmentation filters to enable automatic subcortical brain area segmentation.
	ISBR and ABIDE (17 different sites)	End to End	categorized subcortical brain areas automatically using FCN and 3D convolutional filters.

The most popular CNN designs are ZFNet, VGGNet, GoogLeNet LeNet, AlexNet, and ResNet, they are put into practice via CNN. The most often used CNNs for image segmentation are U-Net, SegNet, and ResNet18 [18].

Yann LeCun created LeNet, the first popular instance of a network of convolutions, in the 1990s [19]. For instance, the LeNet architecture is employed for decoding zip codes and digits. One of the LeNet models that can recognize a single character with 99.2% accuracy is LeNet-5, a CNN model with five layers.

Table 3: Different CNN architectures are examined [5]

Architectures	Layers	Advantages	Disadvantages
LeNet-5	7Layers	Larger, stronger layers are required to process higher quality images.	Sometimes overestimation occurs, and there is no built-in way to prevent this.
AlexNet	8 Layers 60M Parameters	A extremely quick downsampling of the intermediate representations using maxpooling layers and convolutions	Soon after, using huge convolution filters (5x5) is discouraged because they are not deep enough compared to other methods.
ZFNet	8 Layers	enhanced image classification rate inaccuracy when compared to the 2012 ILSVR champion AlexNet	Because feature maps are not split between two GPUs, there are many connections between layers.
GoogleNet	22layers 4-5M parameters	In order to provide the network a greater width and depth, the ILSVRC2014 winners reduced the amount of parameters from 60 million (AlexNet) to 4 million.	It somewhat difficult to manage due of its 138 million attributes.
VGGNet	The optimal number of layers between 11 and 19 is 16. 138M parameters	It is now the most popular choice for feature extraction from photos.	Has 138 million parameters, making it somewhat difficult to manage.
ResNet	152 layers	The network learns the difference to an identity mapping (residual); if the identify is nearer the optimal, the convergence is faster.	Overfitting would increase testing but decrease training error; it is less complex than VGGNet.

The first widely used convolutional network was the AlexNet, created by Alex Krizhevsky [16]. With eight major layers altogether, AlexNet's initial five layers are convolutional layers and its final three levels are fully linked layers. ReLU is utilized in order to improve AlexNet's speed and accuracy. Microsoft Research introduced the ResNet, or residual neural network, in [17]. In ResNet, layers are reformulated while learning functions. As network depth increases, residual networks become more accurate and are simpler to optimize. GoogleNet has 22 layers and was created by Szegedy etal. [10]. It is far more in-depth than AlexNet. AlexNet has sixty million parameters, whereas GoogleNet has four million. Inception-v4 is one of the most popular GoogleNet versions. A comparison of CNN designs is shown in Table 2, and a number of examples of medical CNN architectures are shown in Table 3.

Table 4: CNN's design and its goals [8].

Design	Target	Accuracy
LeNet-5	Tensorflow detection of brain tumors	99%
	Sort the brain of an Alzheimer's patient.	96.85%
AlexNet	X-ray of lung nodules in the chest	64.86%
	Thyroid Ultrasound Image Diagnosis	90.8%
VGGNet-16	Skin lesion taxonomy	96.86%
	Categories of brain tumors	84%
GoogleNet	Identifying Prostate Cancer	95%
	Classification of thyroid nodules on ultrasound pictures	98.29%
ResNet	X-ray of lung nodules in the chest	68.92%
	Category of brain tumors	89.93%
	Diagnosis of pancreatic tumors	91%
ZefNet	The developments and obstacles facing deep learning's edge reconfigurable platforms in the future	-

A variety of postprocessing techniques were suggested in order to refine the prediction results of CNNs in network designs. Architecture of CNN and their targets are tabulated in Table 4. For example, 3D-CRF was selected in [7] for postprocessing, which reduces each voxel's Gibbs energy to correct segmentation findings.

Table 5: CNN methods in medical domain [11].

Features	Methods	Testing Sample	Achievement	Accuracy
Type, size, shape, tumor features	DCNN and googleNet	Thyroid nodules	Improving the performance of fine tuning and argumenting the image samples	98.29%
Size, tumor features, doughnut shaped lesion	FCN, VGG-16, U-Net	Colorectal tumors	Can remodel the current, time-consuming and non reproducible manual segmentation method.	-
Type, size	ResNet18, ResNet34, ResNet52 and Inception-ResNet	Pancreatic Tumors	ResNet18 with the proposed weighted loss function method achieves the best results to classify tumors	91%
Type, size, shape	CNN and LeNet-5	Alzheimer's disease classification	Possible togeneralize this method to predict different stages of Alzheimer's disease for different age groups.	96.85%
Type color image lesions	Transfer learning and Alex-net	Skin lesions classification	Higher performance than existing methods	96.86%
Image lesion, type	VGGNet and patch-based DCNN	Prostate cancer	Enhanced prediction	95%
Textures	AlexNet	Breast Cancer	Showed that accuracy obtained by CNN on BreaKHis dataset was improved	-

Furthermore, based on the voxel intensities and tumor area volume, Havaei [4] provided precise forecasts that are out of the ordinary in areas around the skull. In [16], a more intricate post-processing pipeline that depends on the volume of the anticipated region, the voxel intensity, and other factors is provided. For the purpose of pulmonary nodule identification, Setio et al. [17] employed multi-view convolutional networks, using a network architecture made up of multi-stream 2D CNNs.

Breast cancer is the second leading cause of cancer-related mortality in the United States. Breast cancer mortality is decreased with mammography screening. CNN Medical methods in medical domain collected and tabulated in Table 5. To increase guessing accuracy in mammography screening, the CAD system is utilized. Convolutional layers make up the input of a contemporary CNN, whereas one or more fully connected (FC) layers make up the output. VGG and residual (Resnet) networks were compared to CNN techniques in the Shen et al. [63] research. With an emphasis on reliability and categorization enhancements, this table presents a variety of models and performance metrics that highlight current developments in machine learning-based brain cancer diagnosis.

To reduce the characteristics chart, a visual geometry group (VGG) block stacks several 3 ~ 3 convolutional layers using 2 × max pooling. The performance of the final classifiers depends on how well the patch classifier's function. Colorectal cancer (CRC) is the third most common cancer diagnosed [28]. MRI has specific benefits when it comes to determining the precise location of tumors in cancer of the colon.

In order to extract features from an image of a colorectal tumor, the primary model utilized in [30] was VGG-16. Five side-output blocks were utilized for data categorization and localization. Table 6 discusses CNN techniques in medicine.

Table 6: Current brain cancer detection research

Year	Method	Algorithm/ Model	Dataset	Accuracy/ Performance	Highlights
2020	Deep Learning	Convolutional Neural Network (CNN)	BRATS Dataset	Accuracy: ~92%	When it comes to automatically segmenting and classifying brain cancers from MRI scans, CNNs perform admirably.
2021	Hybrid Deep Learning	CNN + Recurrent Neural Network (RNN)	BRATS 2020	Accuracy: 93%	Combining CNN for feature extraction and RNN for temporal analysis, enhancing tumor detection in dynamic brain MRIs.
2021	Transfer Learning	VGG16, ResNet50	BRATS Dataset	Accuracy: ~95%	Pretrained models fine-tuned for tumor classification using smaller datasets, reducing training time.
2022	Random Forest (RF)	RF Classifier	Local Hospital Dataset	Accuracy: ~90%	Effective in distinguishing between tumor and non-tumor regions, but less effective with high-dimensional data.
2022	Support Vector Machine (SVM)	SVM Classifier	Public Brain MRI Dataset	Accuracy: 85-88%	Works well for binary classification (benign vs malignant), but struggles with multi-class problems.
2023	Ensemble Learning	Bagging and Boosting (XGBoost)	Multi-center MRI Data	Accuracy: 94%	Improves robustness and reduces overfitting by combining multiple machine learning algorithms.
2023	UNet Architecture	Deep Neural Network (DNN) - UNet	BRATS 2022	Dice Score: 0.87	Highly effective for segmentation tasks, especially in capturing complex tumor shapes and boundaries.
2024	Graph Neural Network (GNN)	GNN Model	BRATS 2023	Accuracy: ~92%	GNN models better capture the spatial relationships in brain tumor data, enhancing segmentation accuracy.
2024	Federated Learning	Collaborative Deep Learning	Multiple MRI Datasets	Accuracy: ~91%	Protects patient privacy by training models across different institutions without sharing data.

5 Conclusion

One of the biggest issues facing modern society is protecting people from known ailments like brain tumors. The latest technological advancements in medical imaging have been influenced by deep learning and other artificial intelligence techniques. Large datasets that are used to train algorithms to detect abnormalities can be reliably analyzed thanks to these methods. Artificial neural networks (ANNs) are a common type of machine learning model used in image processing applications like segmentation and classification.

Other sophisticated CNN models have also been suggested for related applications. Since the objective of image processing techniques is to recover contaminated and abnormal regions from magnetic resonance imaging (MRIs), segmentation is a crucial step. When it comes to pinpointing the exact site of tumors in colon cancer, MRI offers particular advantages. VGG-16 was the main model used in [30] to extract characteristics from a picture of a colorectal tumor. Five side-output blocks were used to localize and categorize the data. CNN approaches in medicine are included in Table 6.

We looked more closely into CNN, examining its various designs and applications in medical imaging. Based on our research, we were able to pinpoint the domain's current issues and provide a list of possible future directions for this topic. This paper focused on the outcomes of different CNN architectures used in medical image processing.

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