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The Role of Machine Learning in the Detection and Classification of Brain Tumors: A Literature Review of the Past Two Years

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Abstract

A brain tumor is an abnormal growth of cells in the brain. There are four common types of brain tumors. Doctors can segment and identify the tumors manually, but it is very time-consuming. There exist automatic segmentation algorithms that can facilitate the process. Deep learning is a new method of creating powerful AI models. As a result, there is a need for automatic segmentation algorithms that can facilitate the process and improve the accuracy of brain tumor detection. Artificial intelligence (AI) and machine learning (ML) have emerged as promising tools for developing such algorithms. In particular, deep learning (DL) methods, such as convolutional neural networks (CNNs), have shown great potential for accurately identifying brain tumors in medical images. This paper presents a literature review of recently published papers (2020-2022) on brain tumor classification and detection using artificial intelligence. The review covers various AI and DL methods, including supervised learning, reinforcement learning, and unsupervised learning. It evaluates their effectiveness in detecting and classifying brain tumors in medical images. The review also discusses the challenges and limitations of these methods, as well as future directions for research in this field.

Keywords: artificial intelligence, BraTS, deep learning, Glioma, image segmentation, meningioma, medical imaging, MRI, reinforcement learning

1. Introduction

1.1 Brain Tumor

A brain tumor is a mass of abnormal cells that cannot be suppressed by the immune system and can cause damage to the brain. There are more than 120 types of brain tumors, and not all brain tumors are cancerous. Some are benign. There are four common types of brain tumors, namely metastatic, cancer that forms elsewhere in the body, meningioma formed in the meninges, glioblastoma that originates in the brain, and astrocytoma is formed in the cerebrum (Johnson et al., 2017). Doctors can identify brain tumors with medical imaging technologies such as magnetic resonance imaging (MRI) methods (Damadian, 1971), computer tomography (CT) (Buzug, 2011), and positron emission tomography (PET) (Muehllehner et al., 2006). MRI is a type of medical imaging that uses a strong magnet and radio waves to create detailed pictures of the inside of your body. It is used to diagnose and treat many health conditions, including cancer. CT scanners use a rotating X-ray tube and a row of detectors to create detailed images of the inside of your body. The images taken from different angles are then processed on a computer using special algorithms to produce cross-sectional images of your body. A PET scan is a medical imaging test that can help diagnose and treat conditions like cancer, heart disease, and stroke. It uses a radioactive drug (tracer) to show both normal and abnormal metabolic activity in the body. Physicians can identify the boundary of the tumor, the type of the brain tumor, the presence of acute intracranial hemorrhage, calcifications, and skeletal anatomy based on the medical images. Although it is possible for doctors to segment and identify the tumors manually, it is very time-consuming. Automatic segmentation algorithms can facilitate the process, but there is currently no gold standard for brain tumor image segmentation and classification (Gore, 2020).

1.2 Machine Learning

Machine Learning (ML) has become a popular area of research; it has the potential to bring major changes in radiology that were previously impossible with traditional methods (El Naqa Issam and Murphy M. J., 2015).

ML can be divided into three sub-fields based on the availability of types of data: supervised learning, unsupervised learning, and reinforcement learning (Ayodele, 2010), as shown in Figure 1. Supervised learning (Cunningham et al., 2008) is a method that can use a set of given data items and output labels to solve a particular task. Such problems might involve classification and regression, depending on the scenario. Supervised learning is generally used in several fields today, including finance, marketing, testing, manufacturing, and others. Unsupervised learning is a data-driven technique that can cluster data based on similarities and differences (Barlow, 1989). It is a beneficial process, and it works by gathering the data items into different groups to identify which ones share similarities. In the end, the data items will have been separated into groups based on these similarities, which results in improved and more efficient analysis. Reinforcement learning (RL), can be described as a trial-and-error approach that acts in a complex, real-world environment (Sutton, R. S., & Barto, A. G., 1999). This method creates an AI model that will iterate over the given task based on the reward mechanism and continuously update itself. The process continues until the model can reliably take actions that lead to positive outcomes.

Deep Learning (DL) (LeCun, Y., Bengio, Y., & Hinton, G., 2015), a subset of ML, is a new method of creating powerful AI models that can learn and capture certain subtle features of the data. Within DL, a convolution neural network (CNN) is a type of model that is used to perform tasks such as image and video analysis. CNNs are often used in computer vision applications, such as object recognition and face detection (Yamashita et al., 2018). Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) that is capable of learning long-term dependencies in data (Hochreiter, S., & Schmidhuber, J., 1997). This makes it well-suited for tasks that require the model to remember and use information from long sequences of input data, such as natural language processing and time series forecasting. In brain tumor classification and detection, LSTM networks can be combined with other networks, such as CNN, to analyze medical images, such as MRI scans, continuously and use the resulting information to classify tumors as benign or malignant. The Bayesian neural network (BNN) is a type of neural network that is trained using Bayesian inference (Kononenko, 1989). This allows the network to make predictions based on uncertain or incomplete information by using probability distributions to represent the uncertainty. When diagnosing brain tumors using MRI images, a Bayesian neural network could be used similarly to a regular neural network by analyzing the MRI scan data and using it to classify tumors as benign or malignant. However, because it is trained using Bayesian inference, the network would be able to incorporate uncertainty and make probabilistic predictions about the likelihood of a tumor being benign or malignant. These improvements in deep learning models allowed researchers to construct neural networks that resemble human behavior when analyzing medical images and they could be useful in helping doctors to more accurately diagnose and treat brain tumors.

1.3 Aim

Due to the nature of neural networks, even slightly adjusted network structures or parameters can cause relatively significant differences in results. Therefore, new methods are constantly being developed and published by researchers each year. A paper related to brain tumor detection and classification from 2020 can easily be outdated now in 2022. It is important to always keep up with new research in this field. The main goal of this literature review paper is to analyze papers published between 2020 and 2022 and identify which newly introduce method yields the best results in terms of accuracy and precision. This paper will be analyzing the pros and cons of the recently developed brain tumor segmentation and classification methods , providing a comprehensive reference for comparing different techniques.

2. Method

2.1 Search Procedure

In the first step of our paper, we determined a list of keywords. The title of the paper must include either the “brain tumor” or “brain cancer”, and additional keywords related to ML such as “artificial intelligence”, “deep learning”, “convolutional neural network”, “machine learning”, and “reinforcement learning”. In our search strategy, we looked for research articles published from 2020 to 2022 on Google Scholar, Scopus, and Web of Science using the Publish or Perish 8 (PoP8) tool (Harzing, 2016). It can search for papers on multiple different sources and export lists of papers in JSON, XML, and other formats, filtered out duplicated papers based on their titles, and categorize them based on the approach that they use. We gathered a total of 1397 papers. While most of them suggest new methods of classification and detection of brain tumors, some are literature review papers that we have to filter out.

2.2 Filtering Procedure

The first step was to remove all papers that are not categorized as “Article” from Scopus and Web of Science (Google Scholar does not support it). This can be easily done by unselecting articles with PoP8. Then we exported the list of papers in JSON format with PoP8 so that we can process them better. After merging the three lists of papers and removing duplicated papers based on the titles, we found, in total, 1249 unique papers and 367 final papers after filtering. To simplify the process of filtering out and categorizing 1249 papers, we wrote a simple script to help us reduce the number greatly. The numbers imply that not every one of the 1249 papers has the keywords we wanted, meaning that the 882 papers were grabbed by PoP8 based on keywords or abstracts but had nothing to do with our purpose. The papers were filtered based on keywords in titles. After this filtering, we reduced the total number to 367 papers; of these, 331 papers are about supervised learning, and 36 papers are about reinforcement learning. We then examined the articles' content manually to ensure that they are not just reviewing other methods but proposing new ones. The final result came in with a total of just 20 papers, 16 papers on supervised learning and 4 papers on reinforcement learning.

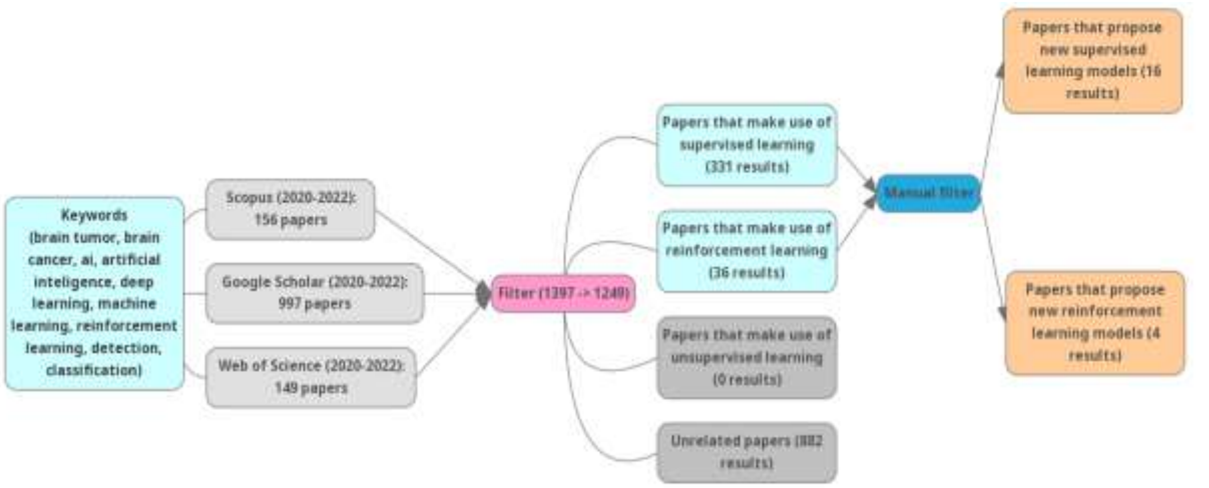

Figure 2. Search strategy and the number of papers left after each step: 1. PoP8 returns results from Scopus, Google Scholar, and Web of Science. 2. Results were merged together and duplicated papers were removed 3. Papers are categorized into three subfields of deep learning, and unrelated papers were disposed of. 4. We manually checked each paper and filtered out remnants.

3. Results

It turns out that there are 2 times as many papers that make use of supervised learning than those that make use of reinforcement learning. 90% of all methods included in this paper are trained with BraTS (Multimodal Brain Tumor Segmentation) datasets from different years, which made it easier for us to compare the validation accuracy of different methods. With that being said, the accuracy numbers presented in the table below should not be used as a factor in determining which method is better since accuracy obtained from different datasets cannot and should not be compared against each other, even if they are from the same domain.

3.1 Supervised Learning-based Approaches

In Brain tumor detection and multi-classification using advanced deep learning techniques (Sadad et al., 2021), Sadad, T., et al. proposed NASNet used ResNet50 as a base and achieved the highest accuracy of 99.6% among MobileNet V2, Inception V3, ResNet50, DenseNet201, NASNet. The model was trained with Adam optimizer and categorical cross-entropy loss, which is very common for classification problems like brain tumor classification. The model was also tested on three separate datasets (BraTS 2015, 2017, 2018), and all yielded accuracies above 90%. In Bayesian Depth-Wise Convolutional Neural Network Design for Brain Tumor MRI Classification (Ekong et al., 2022), Ekong, F., et al. recently proposed a model for brain tumor segmentation & classification based on Bayesian Neural Network. After experimental analysis, they find that their proposed model outperforms these existing models in terms of validation accuracy, training accuracy, F1-score, recall, and precision. The model achieved a training accuracy of 99.03% and a validation accuracy of 94.32%, with F1-score, precision, and recall values of 0.94, 0.95, and 0.94, respectively. The authors claim that this is the first neural network model that combines the effects of depth-wise separable convolutions with the Bayesian algorithm using encoders. In Microscopic brain tumor detection and classification using 3D CNN and feature selection architecture (Rehman et al., 2021), Rehman, A., et al. used the traditional CNN-based feature extraction model. The proposed method is tested on three BraTS datasets from 2015, 2017, and 2018 and achieves accuracies of 98.32%, 96.97%, and 92.67%, respectively. In Automated glioma grading on conventional MRI images using deep convolutional neural networks (Younis et al., 2020), Younis, A., et al. proposed two novel methods for automatically distinguishing between low-grade (grades II and III) gliomas and high-grade (grade IV) gliomas on conventional MRI images using CNNs. The paper reports that both methods performed well in tests, with high sensitivity, specificity, and accuracy (94.7%). In Brain Tumor Analysis Using Deep Learning and VGG-16 Ensembling Learning Approaches (Zhuge et al., 2022), Zhuge, Y. et al. utilized ensemble learning to combine CNN with VGG-16 and bidirectional Long short-term memory (LSTM) layer and proposed two novel methods for non-invasively distinguishing between low-grade and high-grade gliomas using conventional MRI scans. The methods use CNNs for brain tumor segmentation and classification and achieved an accuracy of 98.5% on the BraTS 2013 dataset. In A Hybrid Deep Learning Model for Brain Tumour Classification (Rasool et al., 2022), Rasool, M., et al. proposed an approach that uses two different methods for classification: The first method uses a GoogleNet model that has been pre-trained, combined with a support vector machine (SVM) for classification, while the second one uses a well-tuned GoogleNet model with a soft-max classifier. The approach proposed by Rasool is evaluated using a dataset of MRI brain images containing 708 images of meningioma, 1426 glioma images, 930 pituitary tumor images, and 396 normal brain images. The results show that the proposed approach achieves an accuracy of 93.1% using the well-tuned GoogleNet model and an accuracy of 98.1% using the combination of GoogleNet and SVM. In BrainGAN: Brain MRI Image Generation and Classification Framework Using GAN Architectures and CNN Models (Alrashedy et al., 2022), Alrashedy, H. H. N., et al. propose BrainGAN for generating and classifying brain MRI images using generative adversarial networks (GANs). The proposed framework uses two different GAN architectures, DCGAN and Vanilla GAN, to generate synthetic brain MRI images. These generated images are then used to train and evaluate three different deep learning models: a CNN, MobileNetV2, and ResNet152V2. The results of the experiment show that the ResNet152V2 model outperforms the other two models, achieving an accuracy of 99.09%, precision of 99.12%, 99.08% recall, and 0.196 loss on the generated brain MRI images. In Transfer Learning Based Brain Tumor Detection and Segmentation using Superpixel Technique (Ahuja et al., 2020), Ahuja, S. et al. used a superpixel technique to classify brain images into three categories: normal, low-grade glioma (LGG), and high-grade glioma (HGG). The methodology is tested on the BraTS 2019 challenge database using a VGG-19 transfer learning model. The results show that the proposed approach achieves high accuracy and outperforms existing methods. In Brain Tumor Detection and Classification Using Convolutional Neural Network and Deep Neural Network (Choudhury et al., 2020), C. L. Choudhury et al. proposed a novel model involving the use of a CNN model to classify MRI images as "tumor detected" or "tumor not detected". The model achieved an accuracy score of 96.08% with an f-score of 97.3. The use of automated classification methods using machine learning algorithms, such as CNN, can help address the challenges associated with the manual diagnosis of brain tumors and improve the accuracy of diagnosis. In Brain Tumor Identification and Classification of MRI images using deep learning techniques (Z. Jia and D. Chen, 2020), Z. Jia and D. Chen proposed a fully automatic heterogeneous segmentation method using an SVM for brain tumor segmentation based on deep learning techniques. The method uses structural, morphological, and relaxometry details to accurately segment the venous system in MRI images. The probabilistic neural network classification system is used for training and evaluating the accuracy of tumor detection in images. The results show an accuracy of 98.51% in detecting abnormal and normal tissue from brain MRI images. In BayesCap: A Bayesian Approach to Brain Tumor Classification Using Capsule Networks (P. Afshar, A. Mohammadi and K. N. Plataniotis, 2020), P. Afshar, A. Mohammadi, and K. N. Plataniotis proposed a Bayesian Capsule Network (CapsNet) framework, referred to as BayesCap, for brain tumor classification. CapsNets are powerful architectures for small datasets, such as medical imaging ones, because they are able to capture spatial information between image instances. The BayesCap model is able to provide not only the mean predictions but also entropy as a measure of prediction uncertainty. The maximum accuracy achieved was 73.9%. In Hypergraph membrane system based F2 fully convolutional neural network for brain tumor segmentation (Xue et al., 2020), Xue, J. et al. proposed a novel fully convolutional neural network (FCNN) with a feature reuse module and feature conformity module (FFCN) for accurate brain tumor segmentation. The FFCN extracts more valuable features by repeatedly utilizing features from different layers, eliminates possible noise, and enhances the fusion of different feature map levels. The model achieved an accuracy of 89%. In Deep Learning-Based HCNN and CRF-RRNN Model for Brain Tumor Segmentation (Deng et al., 2020), W. Deng et al. proposed a strategy that uses conditional random fields and heterogeneous convolutional neural networks to achieve the appearance and spatial accuracy. The proposed method involves training the networks with image patches and slices and fine-tuning the model with image slices. Experimental results show that the proposed approach can develop a segmenting model for Flair, T1c, and T2 scans and achieves good performance compared to existing methods. In Brain Tumor Detection Using Artificial Convolutional Neural Networks (S. Irsheidat and R. Duwairi, 2020), S. Irsheidat and R. Duwairi proposed a model based on CNN for the detection of brain tumors using MRI. The model is trained on a dataset of 155 healthy brain MRI images and 98 images containing tumors and is expanded using data augmentation to increase the size of the dataset. The model is able to accurately predict the existence of a tumor, with a validation accuracy of 96.7% and a test accuracy of up to 88.25%. In A deep learning model integrating convolution neural network and multiple kernel K means clustering for segmenting brain tumor in magnetic resonance images (Ragupathy, B., & Karunakaran, M., 2021), Ragupathy, B., & Karunakaran, M. presented an approach that integrates CNN and multiple kernel K-means clustering (MKKMC) to classify MR images as normal or abnormal and to segment the brain tumor from the abnormal images. The proposed algorithm is shown to yield better accuracy (99%) in segmenting brain tumors with less time cost compared to existing methods. In Brain tumor segmentation and classification via adaptive CLFAHE with hybrid classification (Leena, B., & Jayanthi, A., 2020), Leena, B., & Jayanthi, A. presented a new brain tumor classification model that includes five steps: denoising, skull stripping, segmentation, feature extraction, and classification. The performance of the proposed method is 92.15% accuracy.

Table 1. Papers that make use of supervised learning indicating year, publisher, the dataset included along with the achieved accuracy

Year, Publication	Dataset	Technique	Validation accuracy (%)
2021, (Sadad et al., 2021)	BraTs2015, BraTs2017, and BraTs2018.	NASNet	99.6
2022, (Ekong et al., 2022)	BraTs2015	N/A	94.38
2021, (Rehman et al., 2021)	(BraTS) 2015, 2016, and 2017	FNN	98.32
2020, (Younis et al., 2020)	BraTs 2018	3DConvNet	94.7
2022, (Zhuge et al., 2022)	BraTS 2013	VGG-16 Ensemble learning	98.5
2022, (Rasool et al., 2022)	Cheng, J. Brain Tumor Dataset (Cheng, 2017)	CNN-SVM	98.1
2022, (Alrashedy et al., 2022)	BraTs 2015	BrainGAN + ResNet152V2	99.09
2020, (Ahuja et al., 2020)	BraTS 2019	VGG-19 Transfer learning	96.32
2020, (Choudhury et al., 2020)	Gathered from Kaggle	Traditional CNN	96.08
2020, (Z. Jia and D. Chen, 2020)	Not stated	FAHS-SVM	98.51
2020, (P. Afshar, A. Mohammadi and K. N. Plataniotis, 2020)	Benchmark brain cancer dataset	Bayesian CNN (CapsNets)	73.9
2020, (Xue et al., 2020)	BraTS 2015	F2 FCN	89
2020, (Deng et al., 2020)	BraTS 2013	HCNN and CRF-RRNN Model	97
2020, (S. Irsheidat and R. Duwairi, 2020)	253 magnetic resonance image	CNN	96.7
2021, (Ragupathy, B., & Karunakaran, M., 2021)	BraTS 2015	CNN-MKKMC	99
2020,(Leena, B., & Jayanthi, A., 2020)	Cheng, J. Brain Tumor Dataset (Cheng, 2017)	CLFAHE	92.15

3.2 Reinforcement Learning-based Approaches

In A Multi Brain Tumor Classification Using a Deep Reinforcement Learning Model (Kumar B. Anil and Lakshmidevi, N., 2022), Kumar B. Anil and Lakshmidevi, N. use a dataset of 3064 images to train a convolutional neural network to classify tumors into three categories: Glioma, Meningioma, and Pituitary. The results show that reinforcement learning has higher accuracy in tumor classification compared to supervised and unsupervised learning mechanisms. The accuracy of brain tumor classification using reinforcement learning was found to be 95.4%. In Deep reinforcement learning-based image classification achieves perfect testing set accuracy for MRI brain tumors with a training set of only 30 images (Stember, J., & Shalu, H., 2021), Stember, J., & Shalu, H trained a reinforcement learning model on a small dataset of 30 images (15 tumor-containing and 15 normal) and tested it on a different list of 30 images. For comparison, they also trained and tested a supervised DL classification network on the same dataset. The results showed that while the supervised approach overfits the training data and performed poorly on the testing set (57% accuracy), the reinforcement learning approach achieved 100% accuracy on the testing set. In Deep reinforcement learning to detect brain lesions on MRI: a proof-of-concept application of reinforcement learning to medical images (Stember, J., & Shalu, H., 2020), Stember, J., & Shalu, H propose that reinforcement learning can address these issues by providing robust algorithms that can be trained on small datasets. As a proof-of-concept, the authors trained a deep reinforcement learning network on a small dataset of 70 brain MRI images to predict the location of brain tumors. They compared their approach to supervised deep learning and found that reinforcement learning predicted the locations of tumors with 85% accuracy, while supervised deep learning performed poorly with only 7% accuracy. In Deep Reinforcement Learning Classification of Brain Tumors on MRI (Stember, J., & Shalu, H., 2022), Stember Joseph and Shalu, H. trained a deep reinforcement learning model on a small dataset of 30 images (15 normal and 15 tumor-containing), and tested it on a separate set of 30 images. For comparison, they also trained and tested a supervised deep-learning classification network on the same dataset. The results showed that while the supervised approach overfits the training data and performed poorly on the testing set (50% accuracy, equivalent to random guessing), deep reinforcement learning achieved 100% accuracy on the testing set. The authors conclude that deep reinforcement learning can effectively train on relatively smaller data sets and that it learns how to classify images by focusing on the most salient regions.

Table 2. Papers that make use of reinforcement learning indicating year, publisher, the dataset included along with the achieved accuracy

Year, Publication	Dataset	Technique	Validation accuracy(%)
2022, (Kumar, 2022)	BraTs2015, BraTs2017, and BraTs2018.	DQN	95.4
2021, (Stember, J., & Shalu, H., 2021)	BraTs2015	DQN	100
2020, (Stember, J., & Shalu, H., 2020)	(BraTS) 2015, 2016, and 2017	DQN	85
2022, (Stember, J., & Shalu, H., 2022)	BraTs 2018	DQN	100

4. Discussion

Recent advancements in artificial intelligence have led to the development of highly accurate brain tumor segmentation and classification models. These models have shown a high level of reliability in their ability to diagnose brain tumors based on medical images, with many achieving accuracy levels beyond 95%. This level of performance has made it possible for AI to be used in a clinical setting for the analysis of brain tumors, providing a valuable tool for doctors and other medical professionals. However, one of the most apparent similarities the supervised learning-based approaches have in common is that they mostly use CNN network structure as a backbone of the model. Many recent developments in deep learning brain tumor segmentation and classification have focused on improving the performance of neural networks by modifying their architecture, such as using larger networks or adding more layers. However, this brings up the problem that newly proposed approaches are not improving the fundamental algorithm that served as the backbones of supervised learning neural networks. With that being said, many new techniques have been deployed, such as BNN, Generative GAN, and bidirectional LSTM. Some networks incorporate Bayesian methods, allowing them to express uncertainty in their predictions quantitatively, making them well-suited for medical applications where accurate and reliable predictions are critical. On the opposite, reinforcement learning-based approaches are rarely seen in the field of brain tumor classification. This is primarily because reinforcement learning is well-suited for problems where the goal is to find the best sequence of actions to take in order to maximize a reward, such as playing a game or controlling a robot. In contrast, classification problems are typically solved using supervised learning, which involves training a model on a labeled dataset and then using the trained model to predict the class of new, unseen data. In general, reinforcement learning does not bring any extra benefit to the results of classification problems. There are way fewer reinforcement learning-based approaches compared to supervised learning approaches. They achieve 100% accuracy on the test set, which is not necessarily indicative of a well-performing model, as it could be a result of overfitting or other issues. Additionally, it is worth noting that three of these papers were all proposed by the same authors, Kumar B. Anil and Lakshmidevi, N. The authors of these papers argued that reinforcement learning is effective even when trained on small datasets of only 30 images.

In conclusion, the availability of brain medical image data can be a limiting factor for supervised learning-based approaches, as these methods require each image to be manually labeled by a human in order for AI to learn from it. Humans make mistakes from time to time, and those mistakes can potentially contaminate the datasets. Additionally, relying on a single dataset, such as BraTS, can lead to overfitting, where the model performs well on the training data but poorly on new, unseen data. These factors highlight the need for alternative approaches, such as unsupervised learning and reinforcement learning, which may hold the key to future advancements in brain tumor classification. While we did not find any published unsupervised learning-based models from 2020-2022 and only a few reinforcement learning-based models, we believe that further research in these areas has the potential to improve the accuracy and reliability of brain tumor classification.

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