SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V9I12P118

Volume 9 Issue 12, 198-208, December 2022

Original Article

Brain Tumor Detection in MRI Images using Convolutional Neural Network Technique

R. Tamilaruvi[1], R. Vijayalakshmi[2], M. Ganthimathi[3], R. Surendiran[4], M. Thangamani[5], S. Satheesh[6]

[1]*Department of Computer Science and Engineering, Annamalai University, Chidambaram, Tamil Nadu, India*
[2]*Department of Computer Science and Engineering, Velammal College of Engineering and Technology, Madurai, India*
[3]*Department of Computer Engineering, Government Polytechnic College, Dharmapuri, India*
[4]*School of Information Science, Annai College of Arts and Science, Kumbakonam, India*
[5]*Department of Information Technology, Kongu Engineering College, Tamilnadu, India*
[6]*Department of Computer Science and Engineering, Arjun College of Technology, Tamilnadu, India*

[2]*Corresponding Author: rvl@vcet.ac.in*

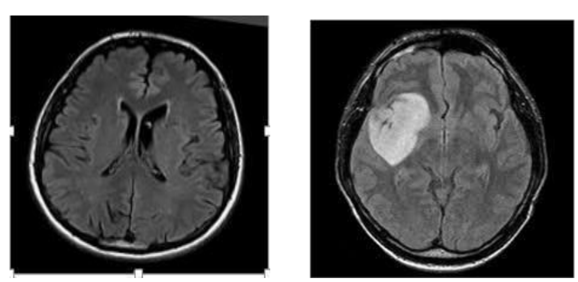
Received: 30 October 2022 Revised: 03 December 2022 Accepted: 19 December 2022 Published: 31 December 2022

Abstract *- A brain tumor is a type of cancer that is difficult to detect. As a result, it is more important for care to evaluate nodules swiftly and appropriately for both men and women. As a result, numerous approaches for detecting brain tumors in their early stages have been developed. A comparative comparison of multiple strategies based on machine learning and deep learning for brain tumor identification has been offered in this procedure. There have been far too many approaches for diagnosing brain tumors developed in recent years, the majority of which rely on MRI images. In addition, several classifier methods are used in conjunction with threshold segmentation algorithms to locate tumors using picture recognition. MRI gray scale images have been discovered to be more suitable for obtaining accurate results because of this method. As a result, most MRI scan images are used to detect tumors in the brain. Furthermore, the findings obtained from approaches based on machine learning and deep learning techniques were more accurate than those obtained from methods based on traditional deep learning techniques. The deep learning method was proposed using the Convolutional neural network to predict the outcome with high accuracy.*

Keywords *- Brain tumor, Convolutional neural network (CNN), Deep learning, MRI(Magnetic Resonance Imaging), Threshold segmentation.*

1. Introduction

In recent years, health informatics systems have been increasingly used to detect and monitor major diseases. Artificial learning-based information systems are used to monitor brain tumor disease. Brain tumors affect both men and women and are caused by uncontrolled cell proliferation in the brain. The brain is the physical body's command and control center. It is responsible for carrying out all activities across many connections and neurons. A brain tumor is one of the most dangerous disorders caused by the abnormal development of cells in the brain that affects the nervous system's activities. Brain tumors come in various shapes and sizes and can be either malignant or benign. Image processing is the process of examining and modifying a photograph to extract information from it. According to figures from the World Health Organization, cancer is the second largest cause of human death worldwide, accounting for an estimated 9:6 million deaths this year. Because of their aggressive nature, varied characteristics (types), and low relative survival rate, brain tumors are often regarded as among the deadliest cancers. The goal of this study is to compile a list of reviews and technical literature on brain cancer diagnosis. It provides an outline of the current brain tumor treatment method. Image processing techniques were used to enhance the brain tumor in an MRI dataset.



Non- brain tumor **Brain tumor**

Fig. 1 Sample dataset MRI brain tumor images

2. Background

2.1. Brain Tumors and Magnetic Resonance Imaging

Brain tumors can be intra-axial (e.g., gliomas) or extra-axial (e.g., meningiomas or pituitary adenomas). Intra-axial brain tumors are particularly difficult to treat, especially at advanced stages, when they are usually discovered due to the symptoms caused by the mass effect on the surrounding brain. Treatment failure can be due to several factors, including the limited capacity of current imaging modalities to identify the boundaries of the lesion within the normal-appearing brain parenchyma. Hence, more advanced imaging techniques for assessing brain tumors and surrounding structures are critical to improving overall management. Extra-axial brain cancers also require special attention, as these tumors (such as pituitary adenoma and meningioma) can result in complications and long-term impairment.

MRI is the workhorse for brain tumor imaging in clinical practice providing structural, microstructural, functional, and metabolic information. Moreover, novel advanced imaging techniques are continuously developed to improve brain tumors' identification, characterization, and response assessment. Hence, much artificial intelligence (AI) applications in brain tumor imaging have been based on MRI.

2.2. Deep Learning

Deep Learning (DL) is a subfield of ML concerned with techniques inspired by neuroscience. However, Good fellow et al. noted that neuroscience is no longer the primary source of inspiration for deep learning. Recently, DL algorithms have established themselves as a critical component of medical image analysis tasks, such as object recognition, classification, and segmentation. CNNs represent the most often utilized DL algorithm for developing brain tumor classification and segmentation techniques. CNNs can learn the spatial relationships between voxels in an MRI scan. In CNNs, multiple filters are hovered on an input image to learn different features that characterize the image.

A typical CNN model mainly consists of the following components: (i) input layer, (ii) convolution layer, (iii) activation function, (iv) pooling layer, (v) fully connected layer, and a (vi) output layer. The input layer feeds the input image into the network for processing by the successive layers. Convolution, pooling, and activation functions are used to extract high-level features from the image, whilst the fully connected layer is used for image classification, object segmentation, or object detection. The output layer generates the network's final prediction or results.

2.3. Vision Transformers

CNNs have demonstrated state-of-the-art performance in computer vision tasks, such as brain tumor segmentation and classification, over the last few years. However, CNNs cannot efficiently capture long-range information or dependencies due to their small kernel size. Long-range dependencies are those in which the desired output depends on image sequences presented at distant times. Due to the similarity of human organs, many visual representations in medical images are organized in sequence. Destruction of these sequences will significantly affect the performance of a CNN model. It is because the dependencies between medical image sequences (such as modality, slice, and patch) contain significant information. These long-range dependencies can be effectively handled by techniques that can process sequence relations. A self-attention mechanism in ViTs has the capacity to model long-range dependencies, which is very important for precise brain tumor segmentation. They achieve this by modelling pairwise interactions between token embedding, thus enabling ViT-based models to learn local and global feature representations. ViT has demonstrated promising performance on a variety of benchmark datasets.

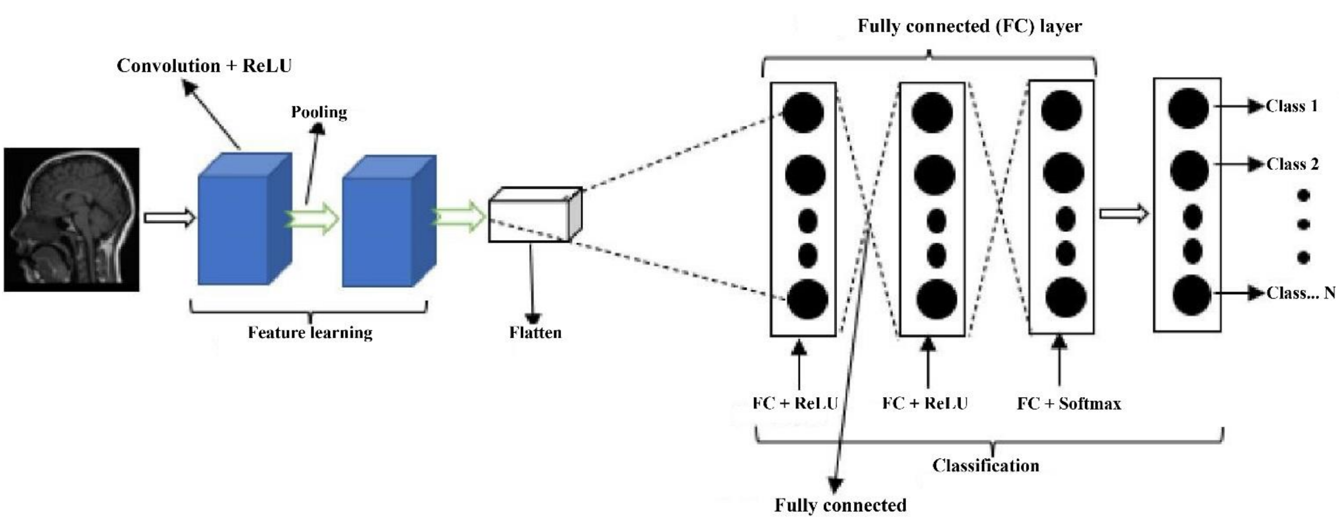


Fig. 2 The general architecture of a Convolutional Neural Network (CNN)

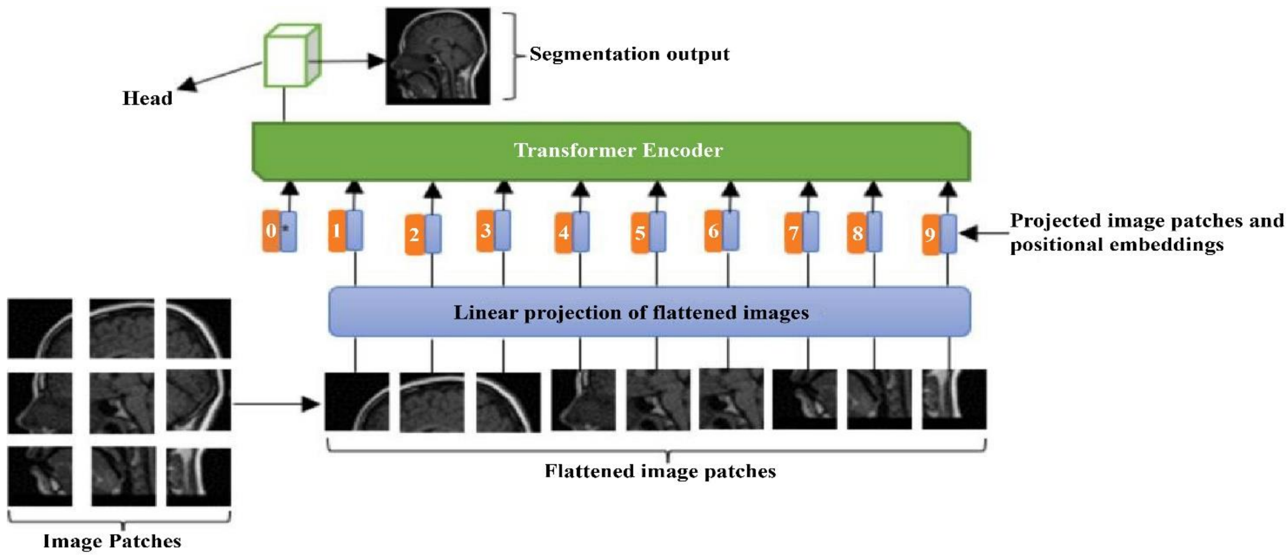


Fig. 3 Vision Transformers (ViT) model

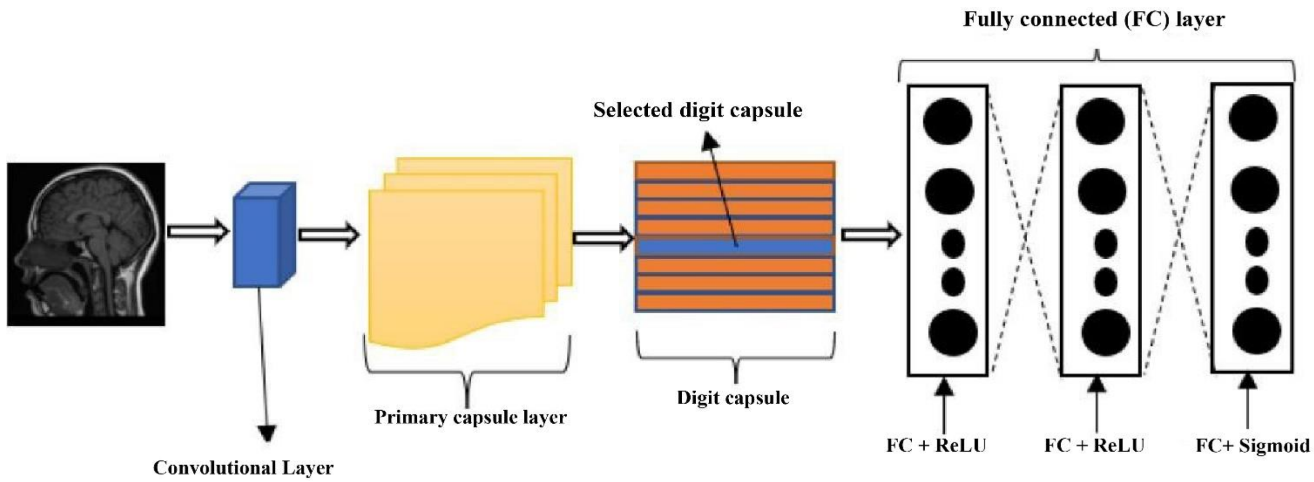


Fig. 4 CapsNet

2.4 Capsule Neural Networks

Despite the remarkable success of CNNs, they have some drawbacks. First, CNNs require vast datasets for training. Second, CNNs are typically not robust to affine rotations and transformations. Additionally, the routing mechanism employed by CNN's pooling layers is distinct from that employed by the human visual system. The CNN pooling layer routes all the information extracted from the image to all the neurons in the subsequent × layer, neglecting essential details or little objects in the image. Hinton et al. designed the CapsNet to address the drawbacks of CNN. The general structure of a CapsNet is depicted in Figure - 4. A CapsNet is a three-layer network composed of the convolutional, primary capsule, and class capsule layers. The primary capsule layer is typically the first one, followed by an undetermined number of capsule layers. The class capsule layer follows the capsule layer. The convolutional layer extracts the feature and then transmits it to the primary capsule layer. The primary capsule performs a series of operations and transmits the resulting feature map to the digit capsule. Typically, the digit capsule is composed of an $n \quad m$ weight matrix, where n denotes the number of classes and m *is* the size of each digit capsule. The digit capsule is used to classify the input image before it is fed into the decoder. The decoder consists of three fully connected layers that are used to reconstruct or decode the selected digit capsule into an image.

Figure 3. Overview of a Vision Transformers (ViT) model. The image is partitioned into N small patches (e.g., 9 patches). Each image patch contains $n \times n$ pixels (e.g., 16 × 16 pixels). After partitioning, each image patch is flattened: each of the flattened image patches is fed into a linear projection layer to obtain a lower-dimensional linear embedding.

Moreover, positional embeddings are added to the sequence of image patches to ensure each image keeps its positional information. The input and position embedded sequences are fed into a standard transformer encoder for training. The training can be conducted by an MLP or CNN head stacked on top of the transformer. The “*” symbol refers to an additional learnable (class) embedding that is appended to the sequence based on the position of the image patch. This class embedding is used to predict the class of an input image after self-attention updates it.

Figure 4. General scheme of a capsule neural network (CapsNet). A CapsNet is a three-layer network composed of the convolutional, primary capsule, and class capsule layers. The primary capsule layer is typically the first one, followed by an undetermined number of capsule layers. The class capsule layer follows the capsule layer. The convolutional layer extracts the feature and then transmits it to the primary capsule layer. The primary capsule performs a series of operations and transmits the resulting feature map to the digit capsule CapsNet can recognize spatial and hierarchical relationships among objects in images. They are resistant to rotation and image transformations. Additionally, as shown in, CapsNet requires substantially less training data than CNN. Moreover, results reported in the literature show that CapsNet has the potential to improve the accuracy of CNN-based brain tumor diagnosis using a minimal number of network parameters.

It is worth noting that the pooling operation in CNNs makes them robust to small input transformations. However, for CNN to perform well, it must be trained on augmented data in terms of scale, rotation, and varying perspectives. Despite this, results reported in the literature indicate that, in some cases, CapsNet performs comparably to CNN models trained on augmented datasets. CapsNet does not need to be trained on large-scale or augmented data to produce excellent results. It makes it a suitable model for medical image datasets, which are typically small. For more information on CapsNet, please refer.

3. Literature Survey

Brain tumors can be located anywhere in the human brain and assume virtually any shape, size, or contrast (dissimilarity). It shows that ML-based solutions that can effectively and automatically classify and segment brain tumors are needed. The introduction of powerful computing devices and lower hardware prices have prompted the scientific community to develop numerous brain tumor segmentation and classification techniques. Some methods were designed with classical ML algorithms, while others were designed with CNN algorithms and CapsNet. This section reviews ML-based, CNN-based, CapsNet-based, and ViT-based brain tumor segmentation and classification techniques. These techniques are expected to assist medical practitioners in improving the accuracy and consistency of diagnosis.

3.1. Classical Machine Learning-Based Techniques

Numerous brain diagnostic systems have been developed using classical ML algorithms, including Support Vector Machines (SVMs), Random Forests (RFs), and k-Nearest Neighbor (kNN), to list a few. These algorithms are used alone or in combination with other ML algorithms or feature selection techniques. This section presents a survey of ML-based brain classification and segmentation techniques.

3.1.1. Brain Tumor Classification and Segmentation Using Hybrid Texture-Based Features

An image's texture is an important feature that can be used to identify different regions of interest. The texture of a region in an image is determined by the distribution of Gray levels across the image pixels. Jena et al.proposed a brain tumor classification and segmentation technique using texture features and multiple ML algorithms. The technique is divided into two stages: tumor classification and tumor segmentation. The MRI scans are pre-processed in the tumor classification stage, and texture features are extracted from the images using different texture extraction techniques. The following texture-based features were explored in the study: first-order statistical feature, Gray- level co-occurrence matrix (GLCM) feature, Gray-level run length matrix (GLRLM) feature, Histogram-oriented gradient (HOG) feature, Local binary patterns (LBP) feature, Cross-diagonal texture matrix (CDTM) feature, and simplified texture spectrum feature. All the features were extracted from 100 tumors and 100 × non-tumor images. The extracted features were combined to form a feature vector matrix size 200 471. Subsequently, the feature vector matrix was used to train five ML algorithms: SVM, k-NN, binary decision trees, RF, and ensemble methods. The ensemble methods consist of seven algorithms: Adaboost, Gentleboost, Logitboost, LPboost, Robust-boost, RUSboost, and Totalboost. After training, the tumorous images were identified and used as input to a hybrid tumor segmentation technique designed for the study. The hybrid technique consists of k-NN and fuzzy C-means clustering algorithms. The hybrid technique was used to segment the tumor regions in the images. It was evaluated on two datasets based on the following performance metrics: average Dice similarity coefficient (DSC), average Jaccard similarity coefficient, and average accuracy. The dataset used to evaluate the model include BraTS2017, BraTS2019, and the Cancer Imaging Archive (TCIA). Experiments show that the ensemble methods produced the best result, achieving a classification accuracy of 96.98% and 97.01% for BraTS2017 + TCIA and BraTS2019 + TCIA, respectively. RF produced the second-best result, achieving an accuracy of 96.5% and 96.99% for BraTS2017 + TCIA and BraTS2019 + TCIA, respectively. The results also show that the segmentation technique produced a Dice similarity score and accuracy of 90.16% and 98.4%, respectively, for BraTS2017.

3.1.2. Brain Tumor Classification Using GoogleNet Features and ML

Sekhar et al. proposed a tumor classification model using a modified GoogleNet pre-trained CNN model and two ML algorithms: SVM and k-NN. In the study, the last three fully connected layers of the GoogleNet network were modified and fine-tuned on brain tumor images. After fine-tuning, the 1024 feature vector from the previous average pooling layer was extracted and used to train SVM and k-NN classifiers. The technique was evaluated on the CE-MRI dataset containing 3064 T_1w post-GBCA brain MR images from 233 patients. Experimental results show that GoogleNet produced precision and recall of 96.02% and 97.00% for glioma, respectively, using the softmax activation function. The model's performance was improved by over 2.5% when the SVM classifier was used. It achieved precision and specificity of 98.76% and 98.93% for glioma, respectively. The performance of GoogleNet was also improved by over 2.3% when the k-NN classifier was used. It produced precision and specificity of 98.41% and 98.63% for glioma, respectively. It shows that features extracted from pre-trained CNN models can be used to build effective ML-based classifiers.

4. Methodology

This review includes papers published between 2019 and 2022. A few studies that were published before 2019 are also covered in this paper. Specifically, we focused on papers that developed brain tumor classification and segmentation approaches using ML, CNN, CapsNet, and ViT. The following databases for scientific literature were queried to find relevant articles: PubMed, Google Scholar, and ScienceDirect. We also queried the online database of the Multidisciplinary Digital Publishing Institute (MDPI) for journal articles. The following search terms were used for our queries: a brain tumor, segmentation, classification, and DL.

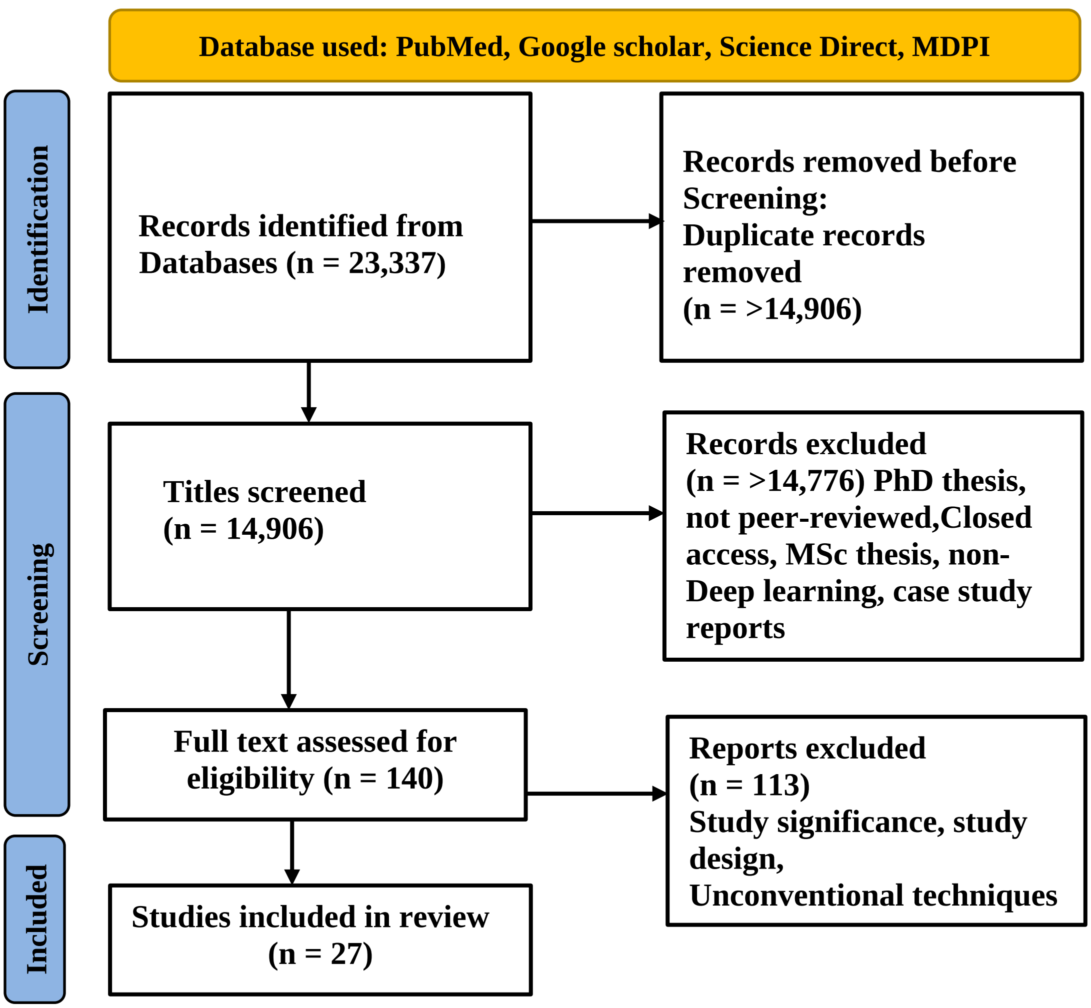
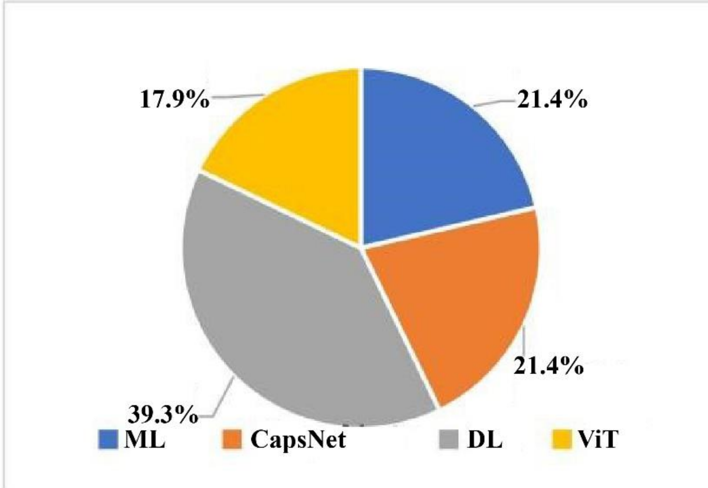
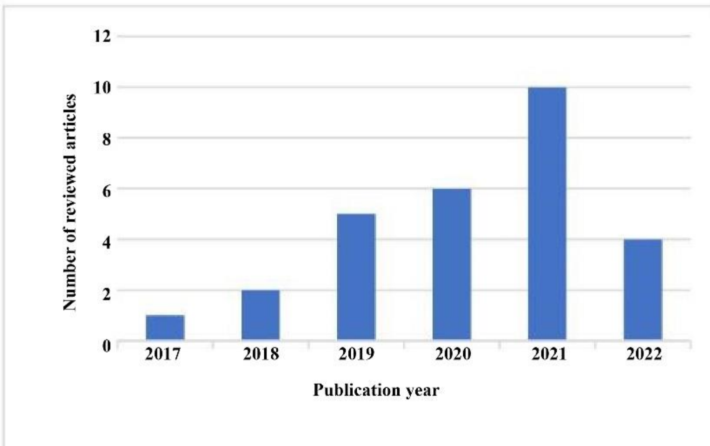


Fig. 5 Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) diagram of the proposed review on AI applications to brain tumor MRI



(a)



(b)

Fig. 6 Percentage of Articles reviewed for this study (a) Segmentation approaches wise (b) Year wise

In addition, the union of the outlined search terms was used with a set of terms relating to DL brain tumor segmentation and classification, including classic machine learning, convolutional neural networks, capsule networks, and transformers. The following inclusion criteria were used in this survey: conventional brain segmentation and classification techniques, deep learning, capsule networks, vision transformers, MRI images, and peer-reviewed. Ph.D. theses, M.Sc. theses, and case study papers were excluded from this study. Figure 5 shows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) diagram used for this survey. Figure 6 a and b illustrates the percentage of articles reviewed in this study and their publication year, respectively.

4.1. Datasets

The 3064 MRI T_1w post-GBCA images from 233 patients were used. The Medical Image Computing and Computer-Assisted Intervention (MICCAI) Society has funded numerous events and open challenges over the years to stimulate the development of DL tools and medical devices for computer-aided diagnosis. Most studies used the datasets provided by the MICCAI Society to evaluate the efficiency of their techniques. Details of the other datasets are also shown in Table 1. As shown in the table, most of the benchmark datasets are small, making it challenging to build DL models from end to end.

4.2. Image Pre-Processing Techniques

Image pre-processing techniques can be used to improve the performance of DL-based techniques. Thaha et al. introduced a skull stripping and image enhancement technique for image pre-processing. Skull stripping removes signals from outside the brain, removing unwanted information and facilitating learning tasks. Image enhancement techniques are also utilized to further increase the image’s quality, allowing for identifying essential features in the image. Sérgio et al. introduced an intensity normalization technique for image pre-processing. Results obtained in the study showed that intensity normalization combined with data augmentation produced good results.

One of the key challenges researchers face applying quantitative analyses to MRI scans is the presence of background interference, such as thermal noise and scanner-related artifacts. Thermal noise is typically triggered by random fluctuations within the MRI system, radiofrequency coils in the MRI scanner, and small movements of the patient during the scanning process. The presence of noise in an MR scan can reduce the quality of the image.

Training a CNN on noisy images can affect its ability to effectively extract tumor-related features, consequently affecting its accuracy and generalization performance. In view of this, some studies adopted denoising and contrast enhancement as pre-processing steps to improve the quality of MRI scans before training CNN models. Some studies also developed other techniques for reducing noise in MR images, including modified median noise filter, Wiener filter, and non-local means approach. More robust and effective denoising techniques are still required.

4.3. Performance Metrics

Several metrics were used to evaluate the performance of ML and DL techniques. Most studies used the Dice similarity coefficient to evaluate the performance of brain tumor segmentation techniques. The coefficients determine the amount of spatial overlap between the ground truth segmentation (X) and the network segmentation (Y). Some studies used average Hausdorff Distance for brain tumor segmentation. Many studies used classification accuracy, precision (or recall), sensitivity, and specificity to evaluate brain tumor classification

4.4. Classification

4.4.1. Convolutional Neural Network (CNN)

CNNs are a sort of deep learning system that uses a grid-like structure to process data. CNNs are a form of deep learning algorithm used to handle data related to space or time. CNNs are similar to other neural networks, but because they use a succession of convolutional layers, they add a layer of complexity. Convolutional layers are an essential part of Convolutional Neural Networks (CNNs). A typical CNN architecture is depicted in the diagram below,

Image identification and classification tasks frequently employ CNNs. CNNs can be used to recognize objects in an image or to classify an image as a cat or a dog, for example. CNNs can also be used to perform more complicated tasks, such as creating visual descriptions or recognizing image points of interest. CNNs can also be used to analyse time-series data like audio or text. CNNs are a strong deep learning tool that delivers cutting-edge outcomes in various applications.

The following are definitions for the various layers in the architecture depicted above:

Convolutional Layer

Convolutional layers are made up of a group of filters (also known as kernels) applied to an input image. A feature map represents the input image with the filters applied as the convolutional layer's output. Layers of convolutional neural networks can be stacked to produce more complicated models that can learn more intricate features from photos.

Pooling Layer

In deep learning, pooling layers are a sort of convolutional layer. The spatial size of the input is reduced by pooling layers, making it easier to process and needing less memory. Pooling also reduces the number of parameters and speeds up the training process. Pooling can be divided into two types: maximum pooling and average pooling. The maximum value from each feature map is used in max pooling, while the average value is used in average pooling. After convolutional layers, pooling layers are often employed to minimise the input size before it is fed into a fully connected layer.

Fully Connected Layer

In a convolutional neural network, fully-connected layers are one of the most fundamental layers (CNN) types. Each neuron in a fully-connected layer is entirely coupled to every other neuron in the previous layer, as the name implies; when the goal is to take the information learnt by the preceding layers and apply them to produce predictions, fully linked layers are often utilized near the conclusion of a CNN.

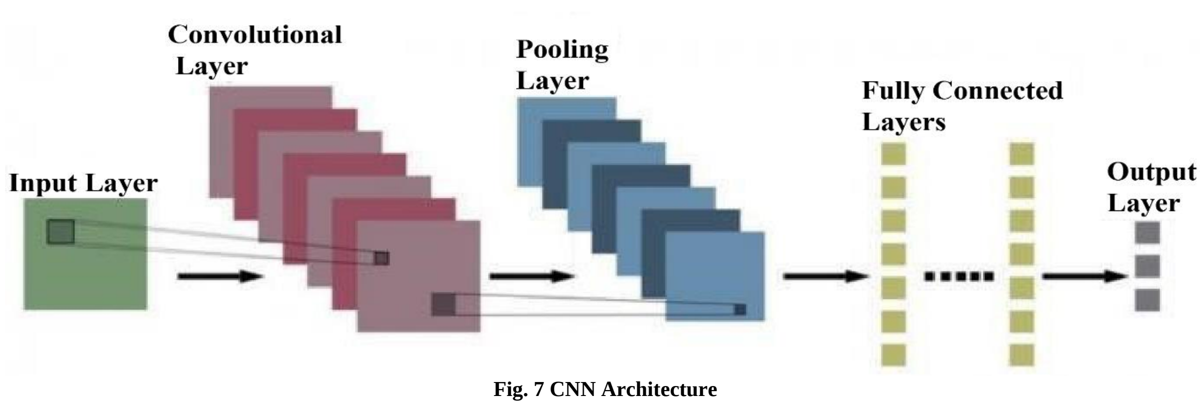


Fig. 7 CNN Architecture

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 65, 65, 32)	416
conv2d_2 (Conv2D)	(None, 65, 65, 32)	4128
batch_normalization_1 (Batch	(None, 65, 65, 32)	128
max_pooling2d_1 (MaxPooling2	(None, 32, 32, 32)	0
dropout_1 (Dropout)	(None, 32, 32, 32)	0
conv2d_3 (Conv2D)	(None, 32, 32, 64)	8256
conv2d_4 (Conv2D)	(None, 32, 32, 64)	16448
batch_normalization_2 (Batch	(None, 32, 32, 64)	256
max_pooling2d_2 (MaxPooling2	(None, 16, 16, 64)	0
dropout_2 (Dropout)	(None, 16, 16, 64)	0
flatten_1 (Flatten)	(None, 16384)	0
dense_1 (Dense)	(None, 512)	8389120
dropout_3 (Dropout)	(None, 512)	0
dense_2 (Dense)	(None, 2)	1026

Total params: 8,419,778
Trainable params: 8,419,586
Non-trainable params: 192

Fig. 8 Layers that are used in our model (II) Prediction

It is a method of predicting brain tumors from a dataset. This project will effectively predict data from the dataset by improving the overall prediction outcomes.

4.5. Result Generation

The overall prediction will be used to create the Final Result. Some measures, such as accuracy, are used to evaluate the performance of this proposed approach.

CNN accuracy is 86.44067645072937 % - 99.98620748519897 % Confidence This is a Tumor

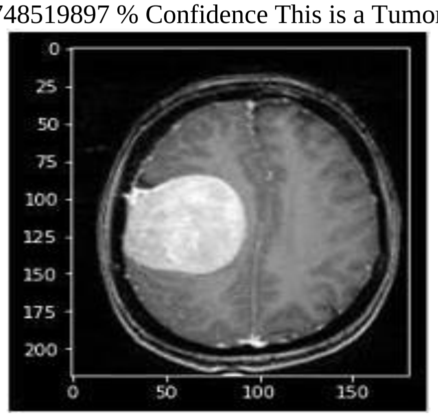


Fig. 9 The accuracy and result for the given input image

It will show the accuracy and result for the given input image (i.e.) whether that selected image has a brain tumor or not.

4.6. Experimental Results

The effectiveness of the proposed technique is assessed using accuracy.

4.6.1. Accuracy

One parameter for evaluating the classification model is accuracy. Accuracy is defined as the ratio of the total number of correct predictions to the total number of predictions.

$$\text{Accuracy} = TP+TN/TP+TN+FN+FP$$

Where,

TP(true positive) is the total number of images correctly classified.

TN(true negative) is the number of images correctly classified but not belonging to that class.

FP(false positive) is the number of images misclassified to some other classes.

FN(false negative) is the number of images belonging to one class but misclassified to another.

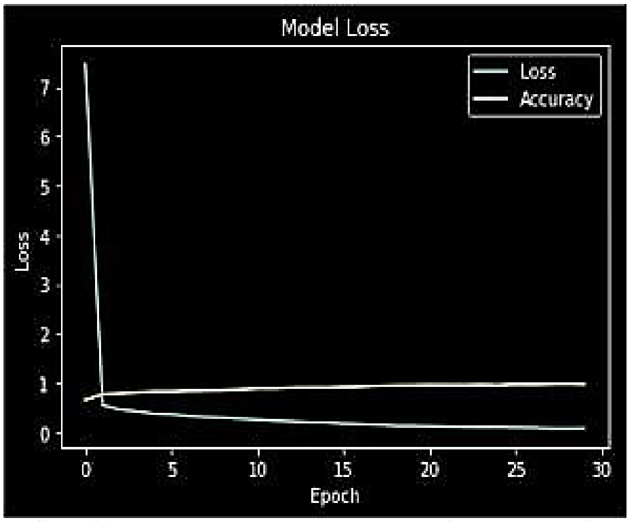


Fig. 10 Graph for accuracy and loss

The accuracy and loss graph denotes the below figure 10.

Here X-axis represents the number of training epochs, and Y-axis represents the model's loss.

5. Conclusion

A two-step approach for detecting brain tumor tissue was introduced in this process. The thresholding approach is combined with using a shape descriptor in this method. The thresholding algorithm groups picture pixels in the first phase, after which the image is binaries using a threshold value. Although tumor structures are formed in binary elements, they are frequently surrounded by healthy structures. The second step eliminates non-tumor tissues, only detecting those corresponding to the tumor. The CNN algorithm can be used to classify MRI images. It will improve the accuracy of brain tumor diagnosis.

References

[1] L. M. De Angelis, “Brain Tumors,” *The New England Journal of Medicine*, vol. 344, no. 2, pp. 114-123, 2001. *Crossref*, https://doi.org/10.1056/nejm200101113440207

[2] Stewart BW, and C. P. Wild, “*World Cancer Report 2014*,” Lyon, France: IARC Publications, 2014.

[3] A.Ratna Raju, P.Suresh, and R.Rajeswara Rao, "Recent Advancements in the Automatic Detection and Segmentation of GBMs from Multimodal Brain MRI Images," *SSRG International Journal of Computer Science and Engineering*, vol. 2, no. 12, pp. 19-23, 2015. *Crossref,* https://doi.org/10.14445/23488387/IJCSE-V2I12P105

[4] Brain, Other CNS and Intracranial Tumours Statistics, 2019. [Online]. Available: https://www.cancerresearchuk.org/

[5] Anthony Behin et al., “Primary Brain Tumours in Adults,” *Lancet,* vol. 361, no. 9354, pp. 323–331, 2003.

[6] Fareed M.mohammed, Mustafa M.Essa, and Ahmed W. Maseer, "Comparison between MRI And CT-Scan in Diagnosis the Brain Tumor Images," *SSRG International Journal of Medical Science*, vol. 6, no. 5, pp. 1-4, 2019. *Crossref,* https://doi.org/10.14445/23939117/IJMS-V6I5P101

[7] Antonios Drevelegas, “*Imaging of Brain Tumors with Histological Correlations*,” Berlin, Germany: Springer, 2002.

[8] T. Gayathri, and K. Sundeep Kumar, "AlexNet – Adaptive Whale Optimization – Multiclass Support Vector Machine model for Brain Tumour Classification," *International Journal of Engineering Trends and Technology*, vol. 70, no. 5, pp. 309-316, 2022. *Crossref,* https://doi.org/10.14445/22315381/IJETT-V70I5P234

[9] Geert Litjens et al., “A Survey on Deep Learning in Medical Image Analysis,” *Medical Image Analysis*, vol. 42, pp. 60–88, 2017. *Crossref,* https://doi.org/10.1016/j.media.2017.07.005

[10] M. L. Goodenberger, and R. B. Jenkins, “Genetics of Adult Glioma,” *Cancer Genetics*, vol. 205, no. 12, pp. 613–621, 2012. *Crossref,* https://doi.org/10.1016/j.cancergen.2012.10.009

[11] D.Napoleon, and M.Praneesh, "Detection of Brain Tumor Using Kernel Induced Possiblistic C-Means Clustering,” *International Journal of Computer Organization Trends and Technology*, vol. 3, no. 5, pp. 40-42, 2013.

[12] David N Louis et al., “The 2016 World Health Organization Classification of Tumors of the Central Nervous System: A Summary,” *Acta Neuropathol*, vol. 131, no. 6, pp. 803–820, Jun. 2016.

[13] Dheeraj D, and Prasantha H S, "DR-UNET: A Hybrid Model For Classification of G lioma using Transfer Learning on MR Images," *International Journal of Engineering Trends and Technology*, vol. 69, no. 10, pp. 146-150, 2021. *Crossref,* https://doi.org/10.14445/22315381/IJETT-V69I10P218

[14] Christopher M. Bishop, “*Pattern Recognition and Machine Learning*,” Berlin, Germany: Springer-Verlag, 2006.

[15] Sindhia et al., "Brain Tumor Detection Using MRI by Classification and Segmentation," *SSRG International Journal of Medical Science*, vol. 6, no. 3, pp. 12-14, 2019. *Crossref,* https://doi.org/10.14445/23939117/IJMS-V6I3P103

[16] T. Rajesh, and R. Suja Mani Malar, “Rough Set Theory and Feed Forward Neural Network Based Brain Tumor Detection in Magnetic Resonance Images,” *International Conference on Advanced Nanomaterials & Emerging Engineering Technologies,* pp. 240–244, 2013. *Crossref,* https://doi.org/10.1109/ICANMEET.2013.6609287

[17] Narendra Mohan, "Tumor Detection From Brain MRI Using Modified Sea Lion Optimization Based Kernel Extreme Learning Algorithm," *International Journal of Engineering Trends and Technology*, vol. 68, no. 9, pp. 84-100, 2020. *Crossref,* https://doi.org/10.14445/22315381/IJETT-V68I9P214

[18] K. Machhale et al., “MRI Brain Cancer Classification Using Hybrid Classifier (SVM- KNN),” *International Conference on Industrial Instrumentation and Control (ICIC)*, pp. 60–65, 2015.

[19] Nidhi Mongoriya, and Vinod Patel, "Review The Breast Cancer Detection Technique Using Hybrid Machine Learning," *SSRG International Journal of Computer Science and Engineering*, vol. 8, no. 6, pp. 5-8, 2021. *Crossref*, https://doi.org/10.14445/23488387/IJCSE-V8I6P102

[20] M. Shasidhar, Sudheer raja Venishetty, and B. Vijaya Kumar, “MRI Brain Image Segmentation Using Modified Fuzzy C-Means Clustering Algorithm,” *Communication Systems and Network Technologies (CSNT), IEEE, Explore*, pp. 473–478, 2011. *Crossref*, http://dx.doi.org/10.1109/CSNT.2011.102

[21] K. Aravinth Raaj, B. Joel Sherwin, and S. Sabeetha Saraswathi, "Automated Detection of Abnormalities in Chest X-Ray Images Using Convolutional Neural Networks,” *International Journal of P2P Network Trends and Technology*, vol. 8, no. 2, pp. 18-24, 2018. *Crossref*, https://doi.org/10.14445/22492615/IJPTT-V8I2P404

[22] Goswami, S, and Lalit Kumar P. Bhaiya, “Brain Tumour Detection Using Unsupervised Learning Based Neural Network,” *2013 International Conference on Communication Systems and Network Technologies, IEEE Explore*, pp. 573–577, 2013.

[23] P.Kanmani, Dr.P.Marikkannu, and M.Brindha, "A Medical Image Classification using ID3 Classifier," *SSRG International Journal of Computer Science and Engineering*, vol. 3, no. 10, pp. 8-11, 2016. *Crossref*, https://doi.org/10.14445/23488387/IJCSE-V3I10P105

[24] S. Khalid, Tehmina Khalil, and Shamila Nasreen, “A Survey of Feature Selection and Feature Extraction Techniques in Machine Learning,” *Science and Information Conference*, pp. 372–378, 2014.

[25] L. Deng, and D. Yu, “Deep Learning: Methods and Applications,” Foundations and Trends in Signal Processing, vol. 7, no. 3–4, pp. 197–387, 2013.

[26] Y. Lecun, Lenet-5, Convolutional Neural Networks, 2015. [Online]. Available: http://yann.lecun.com/exdb/lenet

[27] M. Matsugu, K. Mori, Y. Mitari, and Y. Kaneda, “Subject Independent Facial Expression Recognition with Robust Face Detection Using a Convolutional Neural Network,” *Neural Networks*, vol. 16, no. 5–6, pp. 555–559, 2003. *Crossref*, https://doi.org/10.1016/S0893-6080(03)00115-1

[28] Y. Lecun, Y. Bengio, and G. Hinton, “Deep Learning,” *Nature*, vol. 521, no. 7553, p. 436, 2015. *Crossref*, https://doi.org/10.1038/nature14539

[29] Ibrahima Sory keita et al., "Classification of Benign and Malignant MRIs using SVM Classifier for Brain Tumor Detection," *International Journal of Engineering Trends and Technology*, vol. 70, no. 3, pp. 234-240, 2022. *Crossref*, https://doi.org/10.14445/22315381/IJETT-V70I2P226

[30] Y. Lecun et al., “Gradient-Based Learning Applied to Document Recognition,” *IEEE*, vol. 86, no. 11, pp. 2278–2324, 1998. *Crossref*, https://doi.org/10.1109/5.726791

[31] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet Classification with Deep Convolutional Neural Networks,” *Advances in Neural Information Processing Systems 25 (NIPS 2012)*, pp. 1097–1105, 2012.

[32] Evangelia I Zacharaki et al., “Classification of Brain Tumor Type and Grade Using MRI Texture and Shape in a Machine Learning Scheme,” *Magnetic Resonance in Medicine*, vol. 62, no. 6, pp. 1609–1618, 2009. *Crossref*, https://doi.org/10.1002/mrm.22147

[33] T. Tamilselvi et al., "Deep Derma Scan: A Proactive Diagnosis System for Predicting Malignant Skin Tumor with Deep Learning Mechanisms," *International Journal of Engineering Trends and Technology*, vol. 70, no. 8, pp. 310-317, 2022. *Crossref*, https://doi.org/10.14445/22315381/IJETT-V70I8P232

[34] El-Sayed AhmedEl-Dahshan et al., “Hybrid Intelligent Techniques for MRI Brain Images Classification,” *Digital Signal Processing*, vol. 20, no. 2, pp. 433–441, 2010. *Crossref*, https://doi.org/10.1016/j.dsp.2009.07.002

[35] Jun Cheng et al., “Enhanced Performance of Brain Tumor Classification via Tumor Region Augmentation and Partition,” *PLOS ONE*, vol. 10, no. 10, 2015. *Crossref*, https://doi.org/10.1371/journal.pone.0140381

[36] Rohan K. Gajre, Savita A. Lothe, and Santosh G. Vishwakarma, "Identification of Brain Tumor using Image Processing Technique: Overviews of Methods," *SSRG International Journal of Computer Science and Engineering*, vol. 3, no. 10, pp. 48-52, 2016. *Crossref*, https://doi.org/10.14445/23488387/IJCSE-V3I10P114

[37] Mehmet Günhan Ertosun, and Daniel L Rubin, “Automated Grading of Gliomas Using Deep Learning in Digital Pathology Images: A Modular Approach with Ensemble of Convolutional Neural Networks,” *AMIA Annual Symposium proceedings*, vol. 2015, pp. 1899–1908, 2015.

[38] J. S. Paul et al., “Deep Learning for Brain Tumor Classification,” *Biomedical Applications in Molecular, Structural, and Functional Imaging*, vol. 10137, 2017. *Crossref*, https://doi.org/10.1117/12.2254195

[39] ZENG Runhua, and ZHANG Shuqun, "Improving Speech Emotion Recognition Method of Convolutional Neural Network," *International Journal of Recent Engineering Science*, vol. 5, no. 3, pp. 1-7, 2018. *Crossref*, https://doi.org/10.14445/23497157/IJRES-V5I3P101

[40] Parnian Afshar, Konstantinos N. Plataniotis, and Arash Mohammadi, “Capsule Networks for Brain Tumor Classification Based on MRI Images and Course Tumor Boundaries,” *ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2019.

[41] AminKabir Anaraki, Moosa Ayati, and Foad Kazemi, “Magnetic Resonance Imaging-Based Brain Tumor Grades Classification and Grading Via Convolutional Neural Networks and Genetic Algorithms,” *Biocybernetics Biomedical Engineering*, vol. 39, no. 1, pp. 63–74, 2019. *Crossref*, https://doi.org/10.1016/j.bbe.2018.10.004