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Review Article

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A Survey on Brain Tumor Detection from MRI Images Using Machine Learning Techniques

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Abstract

The accelerated and unchecked cell growth that leads to brain tumors. It can cause death if not treated right away. Accurate segmentation and classification are still challenging tasks, despite significant efforts and encouraging outcomes in this area. The variation in tumor location, shape, and size presents a significant challenge to the detection of brain tumors. In order to help researchers, this survey aimed to compile all available literature on brain tumor detection by magnetic resonance imaging (MRI) images. This research covers a wide range of issues relevant to the study of brain tumors, from tumor anatomy to publicly available datasets to state-of-the-art methodologies to segmentation to feature extraction to classification to machine learning (ML) to transformational learning to quantum ML. Finally, this article grants a thorough analysis of all major publications on brain tumour identification from MRI scans using ML algorithms, including their contributions, limitations, recent advances, and proposed directions for future research.

Keywords

MRI images, Classification, Segmentation, Feature extraction, Machine learning

Introduction

The function of the essential nervous structure is to distribute tactile messages and also the actions that are associated with it to all of the other regions of the body [1-3]. Both the brain and the spinal cord contribute to the transmission of this information throughout the body. The brain stem, the cerebellum, and the cerebellum are the three basic components that contribute to the overall structure of the brain [4]. Depending on a person's gender, the average human brain weighs between 1.2 and 1.4 kg and has a volume that ranges from 1260 to 1130 cm^3 [5]. Problem-solving, motor control, and judgement are only a few of the cognitive functions that are supported by the frontal lobe of the brain. The parietal lobe is responsible for regulating the position of the body. The temporal lobe is in charge of regulating memory as well as hearing function, whereas the occipital lobe is in charge of managing the visual processing in the brain. The neurons that make up the cortex, which is the grey material that covers the outside of the brain [6] are referred to as cortical neurons. When contrasted with the size of the 4,444 cerebella, the size of the cerebellum is more comparable to that of the cerebellum. When it comes to living things, the nervous system is in charge of the process of motor control, which can be defined as the methodical control of movement that has been deliberately initiated. The ALI, Gnb, and LINDA methods were unable to find small lesions because of variable stroke size and territory. In comparison to other species, humans have a well-developed and well-structured cerebellum [7]. Three lobes make up the cerebellum: a front, a back, and a flocculonodular lobe.

The anterior and posterior lobes are connected by a spherical structure known as the vermis. The grey outer cortex of the cerebellum, which is slightly thinner than the cortex, and the inner white matter region make up the structure. Coordinating complicated motor tasks requires cooperation between the brain's frontal and backal lobes. The floculonodular lobe regulates the body's fluid levels and pH [4, 8]. The length of the brain stem, which corresponds to its name, is between 7 and 10 cm. It consists of clusters of cranial and peripheral nerves that aid in breathing and other crucial functions like moving and controlling one's eyes, standing upright, and maintaining balance. The cranial fossa is home to these nerve bundles. It is necessary for nerves to traverse the brain stem enroute from the thalamus to the spinal cord. And then they just started spreading out all over the body. The medulla, the pons, and the midbrain make up the bulk of the brain stem. The midbrain supports processes like eye movements, hearing, and vision. The medulla oblongata aids in controlling blood pressure, swallowing, sneezing, and other bodily functions, while the pons aid in breathing, communication, and sensation in the brain [9].

The examination of the brain during an MRI could be normal or abnormal. The MRI scan of a healthy brain will reveal three distinct types of tissue: grey matter, white matter, and cerebrospinal fluid tissue. Brain scans of tumours frequently show central mass, necrosis, and edema in addition to the previously mentioned normal tissues. While edema is found close to the tumor's active boundary, necrosis occurs within the center of the tumor. Edema, or swelling, is a result of fluid being confined around the tumour. In non-invasive extra-axial tumours like meningiomas, it can cause vasomotor activity, and in invasive tumors like gliomas, it can invade into brain white matter pathways [10, 11]. Furthermore, T1-w, T2-w, and FLAIR are all structural MRI sequences, but they often have trouble differentiating between these tissues due to their similar intensity features. Some sequences are as follows: For instance, it has been discussed [12] how difficult it is to tell a central tumor from an inflammatory lesion that surrounds it. The difficulty of identifying tumours solely based on signal intensity was also demonstrated by [12]. In one case, they showed that two individuals with differing diagnoses of brain tumors shared identical intensity features and significant edema surrounding the tumors. Because of this, they were able to prove that a single patient can develop both forms of brain tumors.

Imaging Modalities in Brain Tumor

Brain tumor analysis frequently involves imaging procedures like positron emission tomography, computed tomography, single photon emission computed tomography (CT), and MRI. Because of their widespread availability and the capacity to produce high-resolution images of both diseased and normal anatomical components, CT and MRI are the technologies most frequently used [13].

MRI

The brain can be seen from three distinct anatomical angles when MRI is performed at varying depths. Axial, longitudinal, and coronal projections are all possible. Variations in image quality, slice thickness, and inter-slice distance have been observed [14, 15] as a function of magnetic field strength and sampling strategy.

Standard anatomical MRI, utilitarian MRI, dispersed imaging, and dispersed tensor imaging are only some of the MRI brain imaging procedures that may be carried out with today's neuroimaging technology [10]. Structural MRI primarily uses the presence or absence of water molecules to differentiate between healthy and diseased brain tissue. This method can be used to map the overall anatomy of vascularization, calcification, and radiation-induced microhemorrhage in brain tumours as well as visualize healthy brain tissue [10, 11].

CT imaging

Images obtained from conventional X-rays cannot compare to the level of detail offered by CT images. Since its inception, the CT scan has been highly endorsed and widely used. The annual number of CT scans in the United States is estimated at 62 million [16], with 4 million of those scans being conducted on children. Different parts of the human body are represented by soft tissues, blood vessels, and bones in CT scans. Contrary to conventional X-rays, it uses more radiation. With repeated CT scans, the radiation can raise the risk of developing cancer. According to the CT radiation dose, cancer-related risks have been calculated [17, 18]. The high contrast between soft tissues provided by MRI allows for the evaluation of structures that are hidden within the scanner and produces anatomical structures that are more clearly defined [19].

Related Works

Segmentation is a crucial process when examining a picture for danger zones. Particular attention should be paid to the use of automatic identification for MRI-based early diagnosis of brain tumors because of the vast practical and diagnostic potential this holds in the medical industry. Figure 1 depicts an MRI of a brain tumor.

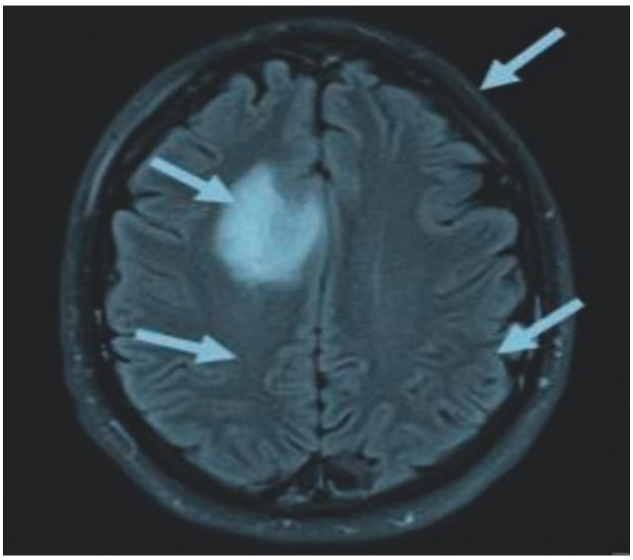

Figure 1: Brain tumor MRI image.

Research is currently being done to improve the independent grading and grading methods for brain tumors so that doctors can more easily diagnose brain tumors. Therefore, a number of research projects have been conducted to learn more about the subject and to review the methods for classifying and segmenting brain tumors. Table 1 only includes a small number of recent publications that are pertinent to our research. Additionally, their benefits and limitations are discussed in detail. Nanoparticles can be developed to detect specific biomarkers associated with diabetes, allowing for early diagnosis and treatments. Targeted medication delivery: Drugs can be packaged onto nanoparticles and administered directly to diseased cells, reducing adverse effects, and increasing therapy success.

Our review aims to provide an extensive overview of recently proposed brain tumor staging and grading methods, such as regional development, shallow ML, and deep learning. Technical issues, such as the advantages and disadvantages of various approaches as well as their effectiveness, are also covered by the work established in this survey.

Literature Survey

In order to detect brain tumors, this section reviews the literature on image preprocessing, feature extraction, segmentation, and classification techniques.

Publicly available datasets

The proposed methods are assessed by researchers using a number of publicly accessible datasets. In this section, a number of significant and difficult datasets will be discussed. The most complicated MRI dataset is BRATS [25]. With more challenges and 1 mm^3 voxel resolution, the BRATS Challenge is released every year. The specifics in table 2 display the dataset.

Literature survey of image preprocessing techniques

MRI image denoising has been researched [27]. The author uses the discrete wavelet transform to denoise the MRI images (DWT). Breakpoints, other self-similar points, and discontinuities in upper derivatives that are ignored by conventional signal analysis techniques can all be dealt with using wavelet analysis.

Table 1: Literature survey on brain tumor detection from MRI images and classification techniques.

Author and publication year	Strength	Limitation
Joo et al. [20] 2022	• Segmentation based on threshold, routine observation, and unattended data. There is a brief explanation of the method.	• Removing the results from the pool of studies used in the analysis. • A basic overview of how brain tumors can be segmented and classified using deep learning.
Chen et al. [21] 2021	• Various types of brain tumors we talked about supervised and unsupervised conventional ML techniques as well as thresholding, region development, atlas, deep learning, and others. • A concise explanation of how well tumor staging techniques work.	• Most peer-reviewed articles on the classification of brain tumors are from 2019 or earlier, arranged chronologically. The only two publications in 2020 are two documents. • When their performance measures are presented, segmentation and classification techniques are not clearly distinguished.
Dixit and Nanda [22] 2021	• Techniques for segmenting brain tumors using ML are described in structure, along with their fundamental components.	• The study did not consider the segmentation performance of the best-performing models on the submitted BRAT dataset. Neither did the commonplace methods of classifying tumors using ML, nor did the more advanced methods of diagnosing brain tumors. Moreover, no brain tumor classification systems were included in the survey.
Sharif et al. [23] 2020	• Brain tumors were described in a thorough and hierarchical classification system. • This article discusses many techniques for segmenting brain tumors, including deep learning, supervised and unsupervised learning, and the use of standard machine thresholds as well as human experts. • Brain tumor categorization strategies based on ML and deep learning have been studied.	• Previous documents prior to 2019 are taken into account in chronological order. • A few deep learning studies using classified documents and brain tumor segmentation are examined.
Ali et al. [24] 2018	• A literature review of the current scientific literature was used to investigate several segmentation algorithms, as well as thresholding, deep learning, and supervised and unsupervised ML approaches.	• We don't discuss the advantages and disadvantages of classification algorithms; rather, we review the literature on the classification of brain tumors. • The review omits information on how well the suggested techniques perform in addition to a brief discussion of brain tumor segmentation methods. • Furthermore, the review work includes records from before 2018.

Table 2: A list of the publicly available datasets.

Datasets	Description	Sequences	Number of slices (images)
BRATS series	Dataset of images from the BRATS 2012 challenge, with five LGG and ten HGG patients' False data set (04LGG, 11HGG) With 285 Participants, the BRATS 2017 challenge has arrived. For the 2018 BRATS competition, 191 participants signed up. 22,877 training and testing slices: BRATS 2019. 25,962 training slices and 25,962 test slices for the BRATS 2020 challenge	Weighted T1, Weighted T1C, Weighted T2, and Flair	240 x 240 x 155
Harvard [26]	A total of 65 tumor pictures and 35 control photos were analyzed	weighted T2	256 x 256 (100 images)
ISLES 2015	64 Subjects	SISS-ISLES CBF, CBV, DI, T1C weighted, T2 weighted, Tmax, TTP; SPESIS-ISLES DI, T1 weighted, T2 weighted, Flair	SISS- ISLES 230 x 230 x 154 (154 slices in each case) SPES-ISLES 230 x 230 x 154 (154 slices in each case)
ISLES 2016	75 Subjects	Tmax, TTP, MTT, rCBV, relative rCBF, and rCBF	192 x 192 x 19 (19 slices in each case)
ISLES 2017	57 Subjects	The PWI, ADC, MTT, rCBV, rCBF, Tmax, and TTP	192 × 192 × 19 (19 slices in each case)

The signal can be compressed and denoised without sacrificing signal quality. The discrete wavelet transform adds more spectral and spatial information while also producing an image without pointless redundancy. It offers information that is richer and more detailed than that offered by a Gaussian or Laplacian pyramid. The low-pass and high-pass filters in the DWT method are in charge of producing the approximation and detail coefficients. Reverse engineering can also be done with DWT, which will perfectly recreate the original signal without sacrificing any of its quality.

The title of an article on how to enhance medical image processing is "Methods to Improve Medical Image Processing" [28]. Signal noise and low contrast issues affect other types of images, such as those used in medical imaging and aerial photography. Image quality can be enhanced in a number of ways, including by lowering the amount of blur in the picture, boosting the contrast and sharpness, and increasing the picture's legibility. Image enhancement techniques include spatial engineering and frequency engineering. Spatial domain techniques, such as negative transform, logarithmic transform, partial clipping, and histogram, have improved the quality of images. Fourier analysis is used to perform a transformation on the current image in order to obtain a smooth image in the frequency domain. These modifications lessen the magnitude of components within a given band of frequencies.

Enhancing and denoising techniques for medical images [29]. The suggested method is broken down into three steps: preprocessing, contrast enhancement, and image denoising. The median filter was used by the authors to lessen the overall amount of noise and increase the clarity near the edges. To improve the contrast of the image in the second stage, histogram equalization is applied. Using the preprocessing method known as histogram equalization, it is possible to guarantee that the grayscale values are distributed uniformly throughout the image. By doing this, you can improve the contrast of an image that looks natural. In order to equalize the histogram of an image, or to make the histogram as flat as possible, the histogram must be stretched. Brain imaging with MRI now offers improved contrast between grey matter, white matter, and cerebrospinal fluid. An image is denoised using a non-local mean filter at the conclusion of the process. Small details can be preserved while noise is reduced. The creator of the non-local media filter claims that in this circumstance, the image bears a striking resemblance to him.

Literature survey of feature extraction techniques

A method for extracting texture information from images was proposed [30]. We extracted the texture properties using the grayscale co-occurrence matrix (GLCM) method. If texture analysis weren't used in the picture alignment process, image analysis' usefulness would be severely constrained. To extract texture characteristics from grayscale images, use the GLCM algorithm. Through the use of these criteria, medical software can categorize conditions as normal or abnormal. Features can be extracted using this statistical technique. By utilizing a matrix, the author was able to assess the image's motion characteristics. Second angular momentum (energy), correlation, and entropy might all be evaluated with the help of MRI scans. In comparison to the discrete wavelet transform, this method uses less time.

A method for locating brain tumors was proposed [31]. The high-resolution images used in this technique have varying contrast levels. For the most part, higher-resolution versions of the original image are produced by oversampling these low-contrast photos with high-contrast ones. Using a patch-based methodology, the algorithm is presented. Using this method, a similar map is produced by comparing the intensity of a single pixel to the intensity of every other pixel in the image. A Gaussian filter was used in these studies by the authors to gather edge data.

A wide range of feature extraction strategies are put to use for classifying data. These techniques include GLCM,

Table 3: An overview of the feature extraction techniques.

Year	Ref.	Dataset	Extracted features	Results
2015	[36]	120 MRI images	Features of GLCM	0.182 extra function, 0.817 PPV, 0.817 overlap function, and 0.817 similarity index
2017	[34]	Private collected images, RID-ER, Harvard	Intensity features, texture, and Shape	When using the SVM (Support vector machine) cubic kernel, the accuracy was 0.79 for photos obtained privately, 0.96 for images obtained through RIDER, and 0.87 for all images
2017	[35]	Harvard	Features of 371 texture and intensity	ACC 0.9334
2018	[33]	ISLES 2015, 2012 Image, 2015 challenge [BRATS], 2013 challenge	GWF, LBP SFTA features, HOG	The equivalent times are as follows: 1.01 on the 2015 ISLES, 0.98 on the 2012 Image, 0.98 on the 2013 Challenge, and 0.98 on the 2015 Challenge
2019	[32]	Privately collected images from the BRATS2013 Challenge and BRATS2015 Challenge	Features that fit the criteria of either LBP, GWF, or both	For BRATS 2013, a merged feature vector (ensemble classifier) using privately obtained photos received 1.00 SP, for BRATS 2015, 0.90 SP, and for BRATS 2017, 0.83 SP, and 0.91 SP
2019	[37]	105 MRI images	Features of GLCM	1.17 Error rate, 1.00 SE, 0.9783 SP, and 0.9882 ACC
2020	[38]	9 BRATS patients from 2015	Features of stochastic textures	0.851 ± 0.093 enhance 0.852 ± 0.063 complete, 0.812 ± 0.074
2020	[39]	BRATS 2015	HOG features, CNN, and LBP	0.76 core, 0.73 enhancement, and 0.81 total
2021	[40]	BRATS 2015	Wavelet transform, (Principal component analysis), mean and entropy	ACC 0.96

geometric features (area, perimeter, and roundness), first-order statistics, GWT, Hu moment invariant, multivariable feature, Haralick 3D features, LBP, GWT, HOG, textures and shapes, co-occurrence matrix, gradients, run length matrix, SFTA, curvature features, and multi-scale text features like Gabor and Gabor. List the feature extraction techniques in table 3.

Literature survey of image segmentation techniques

Using a modified image segmentation method, [12] confirmed that MRI images may be probed to locate brain tumors in patients. The best results were seen using their enhanced probabilistic neural network model that was built on learning vector quantization. Training time was cut in half, classification accuracy was improved, and data processing took 79 percent less time overall. There has been substantial research into the efficacy of linear and Gaussian filters, as well as strategies for augmentation and smoothing. There were multiple epochs when the Canny side detection method was heavily utilized in studies on side detection.

A computer-assisted method of detecting abnormal tissue growth was developed with the hope of improving medical diagnoses. For this method to work, MRI images must be processed as quickly and accurately as possible. As an added bonus, they reduced the amount of noise in the image, making it look better in general. There has been extensive research on the possibility of discontinuous or comparable intensity levels being produced by various imaging modalities for diagnosing brain tumors, as well as morphological and segmentation processing approaches [13].

The use of quantitative methods for automatic feature detection based on the identity of each pixel in an image was shown to improve visual discrimination between scene characteristics and to replace visual analysis of image data with quantitative approaches [18]. Pixel-by-pixel identification is the basis of these quantitative feature detection techniques. These strategies depend on the concept that each visual pixel has a unique identity. On top of that, they demonstrated methods for enhancing the clarity with which one can make out the scene's numerous elements. Data mining through the analysis of digital photographs is another area that has received attention. A team of researchers [19] found that it could use MRI technology to automatically pinpoint the tumor's location in the brain and calculate its volume. As a bonus, they also discovered that the tumor's exact size could be calculated. Using several methods of digital image processing, they showed how to accomplish this task. List the image segmentation techniques in table 4.

Literature survey of classification techniques

Brain cancer classification neural networks [23] that were taught to learn independently. In order to diagnose brain tumors, MRI scans must first be preprocessed, and then tumors must be extracted from the scans. Several methods, including thresholding, edge detection, histogram equalization, and noise filtering, were employed throughout the image's preprocessing phase. ICA was used to identify the distinctive brain feature. The self-organized map is then used to detect and diagnose malignant brain tumors (SOM). The K-means algorithm was used to effectively categorize the brain images into their proper sections. In the preceding section, an experiment was reported that provided evidence that unsupervised learning had promised as a tool for classifying images of brain tumors and, by extension, for segmenting those images.

Brain tumors may be detected and identified automatically [24]. With the use of a multi-stage tumor extraction method, we were able to automatically recognize the tumor in the brain. The noise in brain MRI scans has been reduced. As can be seen in the picture, after that, features were recovered from brain scans that had been cleaned of noise. This newly identified feature was used as the basis for a taxonomy of the brain

Table 4: Overview of unsupervised ML for segmenting brain tumors.

Paper	Dataset	Segmentation technique	Objective function	Performance
[45]	2015 BRATS BRATS-MICCAI	Use of a level-set threshold with multi-level segmentation	Euclidean distance	DSC 89.91%, JI 81.94%
[43]	BRATS	Histogram peak centroid-initialized K-means clustering	Euclidean distance	-
[42]	BRATS 2012	Random	Mean absolute error	DSC 91%
[44]	Author-collected MRI scans	Bi-secting (No initialization)	Total squared error	ACC 83.05%
[46]	Author-collected MRI pictures	DPSO 1	Euclidean distance	DSC 94.09%, SPE 99.92%, SEN 95.02%, ACC 99.98%
[47]	Author-collected MRI pictures	FCM followed by random centroid initialization for segmenting gross tumour volumes	Variation between clusters	SPE 95.31 ± 6.56%, JI 92.81 ± 6.56%, SEN 98.09 ± 1.75%, DSC 95.93 ± 4.23%
[48]	Author-collected MRI pictures	Segmentation based on a semi-automatic cellular automata model with morphological refinement	Calculation of pixel similarity	SPE 99.99 ± 0.01%, JI 84.11 ± 6.74%, SEN 91.20 ± 7.00%, DSC 90.88 ± 4.19%

tumor. To classify neoplasms of the brain, researchers used an ensemble based SVM. When applying the SVM-based classification strategy to the issue at hand, a 99% accuracy rate was feasible. The classification approach employs a number of segmentation techniques to localize the tumor in the brain MRI. Brain tumors, for instance, were retrieved from the afflicted region of the brain after the skull was removed and added to the algorithm via FCM clustering techniques. The skull had already been taken off at this point.

SOM clustering was used to analyze brain pictures for segmentation [25]. To obtain the features, the images are first histogram equalized, and only then are they segmented. Selecting the characteristics required to increase the classifiers' performance was done through principal component analysis. The goal was to boost the classifiers' functionality in this way. When compared to their SVM counterparts, the PSVM classifiers that were constructed simultaneously showed a far better rate of success. Our studies have shown that the SVM classifier is a reliable tool for gleaning useful information from visual data, such as digital images. List the ML based brain tumor classification techniques in table 5.

Discussion on Methodology and Result Analysis

This study analyzed the many approaches taken to classify and divide brain tumors. In this article, we compare and contrast the quantitative results of a number of well-established ML-based methodologies. The conventional image segmentation strategies used in the process of segmenting brain tumors are presented in table 4. Unsupervised ML and region expansion are two examples of such methods. Segmenting brain tumors initially utilized region expanding in addition to conventional methodologies from the field of image processing [56]. Primarily, its overall performance is affected by the noises, the low picture nature, and the basic nut mark. To address these concerns, various strategies have been proposed, including the automatic selection of seed sites via optimization methods and the selection of seed points based on artificial intelligence [57]. By employing these methods, seed point selection might be carried out mechanically. To add insult to injury, it can't tell the difference between tumors in different parts of the brain. Unfortunately, there is an issue with the approaches taken in this

Table 5: An overview of traditional ML-based methods for classifying brain tumors.

Paper	Dataset	Preprocessing	Feature extraction	Classifier	Tumor types	Performance
[49]	Regional data set	Filtering by the median and the Fourier distance	Statistical features, shape features	Artificial Neural Networks	Benign malignant stage (I-IV)	100% SPE, 98% SEN, 97% ACC, and 0.0294% BER
[50]	Regional data set	Modifying the size of the skull	GLCM DWT, Gabor filter	Artificial Neural Networks	Benign and malignant stage (I-IV)	98.5% SPE, 99.1% SEN, and 98.9% ACC
[51]	TCIA	Resizing, cropping, median filtering	Features of shape	K-Nearest Neighbor	Glioblastoma Astrocytoma Oligodendroglioma	ACC 89.5%
[52]	Regional data set	Discretization	Statistical properties of DWT coefficients	SVM	Benign malignant	ACC (kernel) 99%, ACC (linear) 92%
[53]	Regional data set	-	Texture wavelet transform using the gabor	SVM	Pilocytic Ependymoma Astrocytoma	80% SPE, 93% SEN, 88% ACC, and 0.86 AUC
[54]	Local dataset	Size reduction improvement	Statistical texture features using the GLCM	SVM	Malignant, Benign	SPE 62.5%, SEN 88.25%, ACC 89.90%
[55]	Local dataset	Enhancement, noise removal	Statistical features, GA	SVM	Malignant, Benign	SPE 100%, SEN 98%, ACC 98.30%

area. Thanks to the use of second-generation image segmentation algorithms, it is now possible to classify pixels in an image as belonging to more than one of a given set of categories. Fuzzy c-means and fuzzy k-means are two such approaches. Both of these approaches are rooted in what is known as "unsupervised, shallow ML." Unfortunately, the noise in the environment can easily overwhelm these methods. The performance of medical image segmentation can be improved as a result of adaptively selecting the centroid and adding additional information [6]. That's not impossible. (Citation needed for follow-up) There aren't enough references to back up the statements made in this section. In addition, conventional and clustering segmentation methods face significant challenges due to the inherent uncertainty at the boundary between normal tissues and brain tumors. The difficulty arises because of the blurred line between healthy brain tissue and malignant brain tumors. To address this issue, many approaches for pixel-level classification-based segmentation have been developed [58]. These methods rely on supervised ML, which is the most prevalent method currently available. In addition to these methods, feature engineering—which can be thought of as the process of collecting the expressive rubble of data about the tumor to string the framework—is frequently employed. Post-processing can considerably enhance the results of the supervised ML segmentation method [59, 60].

The broad acceptance of ML-based methodology over the past few years has rendered nearly obsolete the use of traditional methods for processing images and superficial ML-based techniques to the segmentation of brain tumors. Also becoming obsolete are the conventional methods of picture processing. Tumor segmentation begins with the processing of an MRI picture and continues through its subsequent analysis using a ML-based technique. Often, these models can automatically capture tumor descriptive information, negating the need to manually include features. However, a large dataset is required for model training, and it might be difficult to evaluate model findings [57]. Because of this, the models can't be used in the healthcare sector. Following post-processing, the ML-based methodology and the controlled superficial ML-based method both give results that are comparable with regard to segmentation, as shown in table 4 and table 5. Several methods were explored in this study for segmenting brain tumors, and a summary of these methods is shown in figure 2.

Histological classification of tumors is crucial for diagnosis and therapy planning in modern medicine [58]. This necessitates a biopsy technique. That's in addition to separating out the tumorous area of the brain on an MRI scan. The advancement of a number of algorithms based on shallow ML has made brain tumor classification much simpler. A typical shallow ML technique consists of three phases: preprocessing, ROI detection, and feature extraction. Due to changes in cell shape, size, position, and contrast between different types of cancer tissue, it may be challenging to acquire descriptive information using MRI image collecting. In sum, these considerations can make it tough. Therefore, ML approaches are quickly replacing traditional methods as the gold standard for categorizing the many subtypes of brain cancer currently in use, including astrocytomas, gliomas, meningiomas, and pituitary tumors. Brain tumors have been classified in a variety of ways throughout this paper's discussion, and an overview of these categorization systems is presented in figure 3.

Classification models were trained and tested using multiple datasets with information unique to brain tumors. Researchers used both proprietary and publicly available datasets in their analyses. A widely used dataset for training and testing classifier models is the publicly available dataset [38]. Meningioma, glioma, and pituitary tumor MRI-images in T1-WC format are all included in this data set. On this dataset, [25] used regularized extreme ML to obtain an accuracy of 94.23% in classification, whereas [53] used a custom-modified deep-dense inception residual network to achieve an accuracy of 99.69% in classification. These numbers were used in the research presented in publications [25] and [53]. The results suggest that ML approaches perform better than shallow ML approaches when used to this dataset.

These small nanoparticles have enormous promise for medication delivery over the blood brain barrier. Beyond medication delivery, nanoparticles can be simulated to generate fluorescence, which can be used to detect cancers. The efficacy of chemotherapeutic treatment or surgical tumor excision is dependent on accurate imaging. Nanomaterials have the potential to improve cancer imaging and therapy [61].

The ineffectiveness of traditional tactics has resulted in the creation of new strategies and the substantial advancement of nanotechnology in recent years. These platforms have the potential to be exploited as novel imaging tools or to increase anticancer drug delivery into tumors while limiting dispersion

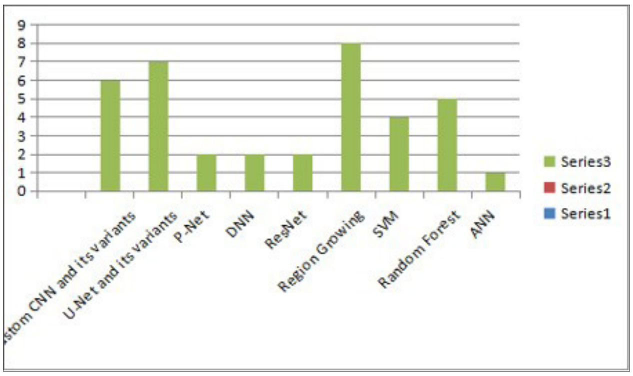

Figure 2: Analysis of segmentation techniques for brain tumors.

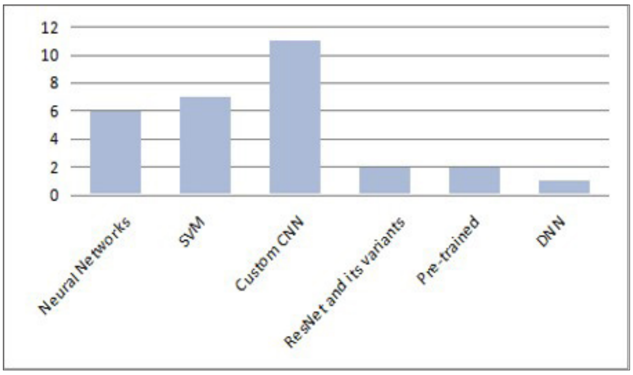

Figure 3: Analysis of classification techniques for brain tumors.

and toxicity in healthy regions. Polymeric nanoparticles, liposomes, dendrimers, nanoshells, carbon nanotubes, superparamagnetic nanoparticles, and nucleic acid-based nanoparticles (DNA, RNA interference, and antisense oligonucleotides) are among the new nanotechnology platforms used for delivery into brain tissue [62].

Conclusion

The appearance of the tumor, as well as its size, shape, and structure, can make an accurate diagnosis of a brain tumor extremely challenging. Even though cancer segmentation algorithms have shown considerable promise for evaluating and detecting tumours in MRI images, much remains to be done to make progress toward accurately segmenting and classifying the tumor region. In particular, when it comes to identifying the underlying components of the tumor location and differentiating between healthy and unhealthy photos, the work that has been done thus far offers both benefits and cons.

This review summarizes the key aspects and the most recent work that has been done to date, along with the limitations and problems associated with each. Gaining an appreciation for how to conduct novel research in a timely fashion would be beneficial to the researchers.

A generic method is still required, notwithstanding the significant progress made by ML strategies. When training and testing, it's important to utilize images with similar acquisition characteristics (intensity range and resolution) because even little differences might have a big effect on the methods' resilience.

Brain tumors will soon be easier to identify thanks to the utilization of real patient data gathered from any source (different picture capturing technologies) (scanners). Combining manually generated attributes with ML features may increase categorization precision. As a result, radiologists' time is saved, and a greater number of patients recover from their illnesses with the help of lightweight technologies such as quantum ML.

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Conflict of Interest

None.

References

1. Park JG, Lee C. 2009. Skull stripping based on region growing for magnetic resonance brain images. *NeuroImage* 47(4): 1394-1407. https://doi.org/10.1016/j.neuroimage.2009.04.047
2. Khan MA, Lali IU, Rehman A, Ishaq M, Sharif M, et al. 2019. Brain tumor detection and classification: a framework of marker-based watershed algorithm and multilevel priority features selection. *Microsc Res Tech* 82(6): 909-922. https://doi.org/10.1002/jemt.23238
3. Raza M, Sharif M, Yasmin M, Masood S, Mohsin S. 2012. Brain image representation and rendering: a survey. *Res J Appl Sci Eng Technol* 4(18): 3274-3282.
4. Watson C, Kirkcaldie M, Paxinos G. 2010. The Brain: An Introduction to Functional Neuroanatomy. Academic Press, New York.
5. Brain Size. [https://en.wikipedia.org/wiki/Brain_size] [Accessed December 05, 2023]
6. Dubin MW. 2013. How the Brain Works. John Wiley & Sons.
7. Koziol LF, Budding DE, Chidekel D. 2012. From movement to thought: executive function, embodied cognition, and the cerebellum. *Cerebellum* 11(2): 505-525. https://doi.org/10.1007/s12311-011-0321-y
8. Strick PL, Dum RP, Fiez JA. 2009. Cerebellum and nonmotor function. *Annu Rev Neurosci* 32: 413-434. https://doi.org/10.1146/annurev.neuro.31.060407.125606
9. Nuñez MA, Miranda JCF, de Oliveira E, Rubino PA, Voscoboinik S, et al. 2019. Brain Stem Anatomy and Surgical Approaches. In Chaichana K, Quiñones-Hinojosa A (eds) Comprehensive Overview of Modern Surgical Approaches to Intrinsic Brain Tumors. Academic Press, pp 53-105.
10. Villanueva-Meyer JE, Mabray MC, Cha S. 2017. Current clinical brain tumor imaging. *Neurosurgery* 81(3): 397-415. https://doi.org/10.1093/neuros/nyx103
11. Neuroradiology: Anatomy Index. [https://radiologyassistant.nl/neuroradiology/brain] [Accessed December 05, 2023]
12. Alves AFF, Miranda JRDA, Reis F, Souza SASD, Alves LLR, et al. 2020. Inflammatory lesions and brain tumors: is it possible to differentiate them based on texture features in magnetic resonance imaging? *J Venom Anim Toxins Incl Trop Dis* 26: e20200011. https://doi.org/10.1590/1678-9199-JVATITD-2020-0011
13. Kasban H, El-Bendary MAM, Salama DH. 2015. A comparative study of medical imaging techniques. *Int J Inf Sci Intell Syst* 4(2): 37-58.
14. Ammari S, Pitre-Champagnat S, Dercle L, Chouzenoux E, Moalla S, et al. 2021. Influence of magnetic field strength on magnetic resonance imaging radiomics features in brain imaging, an *in vitro* and *in vivo* study. *Front Oncol* 10: 541663. https://doi.org/10.3389/fonc.2020.541663
15. Rajasekaran KA, Gounder CC. 2018. Advanced Brain Tumour Segmentation from MRI Images. In Halefoğlu AM (ed) High-Resolution Neuroimaging - Basic Physical Principles and Clinical Applications. IntechOpen.
16. Smith-Bindman R, Lipson J, Marcus R, Kim KP, Mahesh M, et al. 2009. Radiation dose associated with common computed tomography examinations and the associated lifetime attributable risk of cancer. *Arch Intern Med* 169(22): 2078-2086. https://doi.org/10.1001/archinternmed.2009.427
17. Fink JR, Muzi M, Peck M, Krohn KA. 2015. Multimodality brain tumor imaging: MR imaging, PET, and PET/MR imaging. *J Nucl Med* 56(10): 1554-1561. https://doi.org/10.2967/jnumed.113.131516
18. Exploring the Brain: Is CT or MRI Better for Brain Imaging? [https://radiology.ucsf.edu/blog/neuroradiology/exploring-the-brain-is-ct-or-mri-better-for-brain-imaging] [Accessed December 05, 2023]
19. Khan MA, Arshad H, Nisar W, Javed MY, Sharif M. 2021. An Integrated Design of Fuzzy C-Means and NCA-Based Multi-properties Feature Reduction for Brain Tumor Recognition. In Priya E, Rajinikanth V (eds) Signal and Image Processing Techniques for the Development of Intelligent Healthcare Systems. Springer, Singapore, pp 1-28.
20. Joo L, Jung SC, Lee H, Park SY, Kim M, et al. 2021. Stability of MRI radiomic features according to various imaging parameters in fast scanned T2-FLAIR for acute ischemic stroke patients. *Sci Rep* 11(1): 17143. https://doi.org/10.1038/s41598-021-96621-z
21. Chen H, Zou Q, Wang Q. 2021. Clinical manifestations of ultrasonic virtual reality in the diagnosis and treatment of cardiovascular diseases. *J Healthc Eng* 2021: 1746945. https://doi.org/10.1155/2021/1746945
22. Dixit A, Nanda A. 2022. An improved whale optimization algorithm-based radial neural network for multi-grade brain tumor classification. *Visual Comput* 38(11): 3525-3540. https://doi.org/10.1007/s00371-021-02176-5

23. Sharif M, Amin J, Raza M, Anjum MA, Afzal H, et al. 2020. Brain tumor detection based on extreme learning. *Neural Comput Appl* 32: 15975-15987. https://doi.org/10.1007/s00521-019-04679-8

24. Ali AH, Al-hadi SA, Naeemah MR, Mazher AN. 2019. Classification of brain lesion using K-nearest neighbor technique and texture analysis. *J Phys Conf Ser* 1178: 012018. https://doi.org/10.1088/1742-6596/1178/1/012018

25. Menze BH, Jakab A, Bauer S, Kalpathy-Cramer J, Farahani K, et al. 2014. The multimodal brain tumor image segmentation benchmark (BRATS). *IEEE Trans Med Imaging* 34(10): 1993-2024. https://doi.org/10.1109/TMI.2014.2377694

26. Summers D. 2003. Harvard whole brain atlas: www.med.harvard.edu/aanlib/home.html. *J Neurol Neurosurg Psychiatry* 74(3): 288. https://doi.org/10.1136/jnnp.74.3.288

27. Agrawal S, Sahu R. 2012. Wavelet based MRI image denoising using thresholding techniques. *Int J Sci Eng Technol Res* 1(3): 32-35.

28. Singh G, Mittal A. 2014. Various image enhancement techniques - a critical review. *Int J Innov Sci Res* 10(2): 267-274.

29. Mathen SJ, George A. 2014. Analysis of MRI enhancement techniques for contrast improvement and denoising. *Int J Curr Eng Technol* 4(6): 3853-3861.

30. Mohanaiah P, Sathyanarayana P, GuruKumar L. 2013. Image texture feature extraction using GLCM approach. *Int J Sci Res Publ* 3(5): 1-5.

31. Jafari-Khouzani K. 2014. MRI upsampling using feature-based non-local means approach. *IEEE Trans Med Imaging* 33(10): 1969-1985. https://doi.org/10.1109/TMI.2014.2329271

32. Amin J, Sharif M, Raza M, Saba T, Sial R, et al. 2020. Brain tumor detection: a long short-term memory (LSTM)-based learning model. *Neural Comput Appl* 32: 15965-15973. https://doi.org/10.1007/s00521-019-04650-7

33. Amin J, Sharif M, Raza M, Yasmin M. 2018. Detection of brain tumor based on features fusion and machine learning. *J Ambient Intell Hum Comput* 1-17. https://doi.org/10.1007/s12652-018-1092-9

34. Amin J, Sharif M, Yasmin M, Fernandes SL. 2020. A distinctive approach in brain tumor detection and classification using MRI. *Pattern Recogn Lett* 139: 118-127. https://doi.org/10.1016/j.patrec.2017.10.036

35. Tiwari P, Sachdeva J, Ahuja CK, Khandelwal N. 2017. Computer aided diagnosis system - a decision support system for clinical diagnosis of brain tumours. *Int J Comput Intell Syst* 10(1): 104.

36. Shanthakumar P, Ganeshkumar P. 2015. Performance analysis of classifier for brain tumor detection and diagnosis. *Comput Electr Eng* 45: 302-311. https://doi.org/10.1016/j.compeleceng.2015.05.011

37. Srinivas B, Rao GS. 2019. Performance Evaluation of Fuzzy C Means Segmentation and Support Vector Machine Classification for MRI Brain Tumor. In Bansal J, Das K, Nagar A, Deep K, Ojha A (eds) Soft Computing for Problem Solving. Advances in Intelligent Systems and Computing. Springer, Singapore, pp 355-367.

38. Pei L, Bakas S, Vossough A, Reza SM, Davatzikos C, et al. 2020. Longitudinal brain tumor segmentation prediction in MRI using feature and label fusion. *Biomed Signal Process Control* 55: 101648. https://doi.org/10.1016/j.bspc.2019.101648

39. Khan H, Shah PM, Shah MA, ul Islam S, Rodrigues JJ. 2020. Cascading handcrafted features and convolutional neural network for IoT-enabled brain tumor segmentation. *Comput Commun* 153: 196-207. https://doi.org/10.1016/j.comcom.2020.01.013

40. Kaur P, Singh RK. 2023. A review on optimization techniques for medical image analysis. *Concurrency Comput Pract Experience* 35(1): e7443. https://doi.org/10.1002/cpe.7443

41. Dahab DA, Ghoniemy SS, Selim GM. 2012. Automated brain tumor detection and identification using image processing and probabilistic neural network techniques. *Int J Image Process Visual Commun* 1(2): 1-8.

42. Leela GA, Kumari HV. 2014. Morphological approach for the detection of brain tumour and cancer cells. *J Electron Commun Eng Res* 2(1): 7-12.

43. Soni M, Khare A, Jain S. 2014. A survey of digital image processing and its problem. *Int J Sci Res Publ* 4(2): 1-6.

44. Hemalatha C, Muruganand S, Maheswaran R. 2014. Preprocessing methods to remove impulse noise in avian pox affected Hen Image using image processing. *Int J Comput Appl* 98(20): 18-21.

45. Rajinikanth V, Fernandes SL, Bhushan B, Harisha, Sunder NR. 2018. Segmentation and Analysis of Brain Tumor Using Tsallis Entropy and Regularised Level Set. In Satapathy S, Bhateja V, Chowdary P, Chakravarthy V, Anguera J (eds) Proceedings of 2nd International Conference on Micro-Electronics, Electromagnetics and Telecommunications. Lecture Notes in Electrical Engineering. Springer, Singapore, pp 313-321.

46. Mehidi I, Belkhiat DEC, Jabri D. 2019. An improved clustering method based on K-means algorithm for MRI brain tumor segmentation. In 6th International Conference on Image and Signal Processing and their Applications, Mostaganem, Algeria.

47. Rundo L, Militello C, Tangherloni A, Russo G, Vitabile S, et al. 2018. NeXt for neuro-radiosurgery: a fully automatic approach for necrosis extraction in brain tumor MRI using an unsupervised machine learning technique. *Int J Imaging Syst Technol* 28(1): 21-37. https://doi.org/10.1002/ima.22253

48. Rundo L, Militello C, Russo G, Vitabile S, Gilardi MC, et al. 2018. GTV cut for neuro-radiosurgery treatment planning: an MRI brain cancer seeded image segmentation method based on a cellular automata model. *Nat Comput* 17: 521-536. https://doi.org/10.1007/s11047-017-9636-z

49. Ahmmed R, Swakshar AS, Hossain MF, Rafiq MA. 2017. Classification of tumors and it stages in brain MRI using support vector machine and artificial neural network. In International Conference on Electrical, Computer and Communication Engineering, Cox's Bazar, Bangladesh.

50. Sathi KA, Islam MS. 2020. Hybrid feature extraction based brain tumor classification using an artificial neural network. In IEEE 5th International Conference on Computing Communication and Automation, Greater Noida, India.

51. Ramdlon RH, Kusumaningtyas EM, Karlita T. 2019. Brain tumor classification using MRI images with K-nearest neighbor method. In International Electronics Symposium, Surabaya, Indonesia.

52. Gurbină M, Lascu M, Lascu D. 2019. Tumor detection and classification of MRI brain image using different wavelet transforms and support vector machines. In 42nd International Conference on Telecommunications and Signal Processing, Budapest, Hungary.

53. Li M, Wang H, Shang Z, Yang Z, Zhang Y, et al. 2020. Ependymoma and pilocytic astrocytoma: differentiation using radiomics approach based on machine learning. *J Clin Neurosci* 78: 175-180. https://doi.org/10.1016/j.jocn.2020.04.080

54. Gayathri S, Wise DJW, Janani V, Eleaswari M, Hema S. 2020. Analyzing, detecting and automatic classification of different stages of brain tumor using region segmentation and support vector machine. In International Conference on Electronics and Sustainable Communication Systems, Coimbatore, Tamil Nadu, India.

55. Sarkar A, Maniruzzaman M, Ahsan MS, Ahmad M, Kadir MI, et al. 2020. Identification and classification of brain tumor from MRI with feature extraction by support vector machine. In International Conference for Emerging Technology, Belgaum, Karnataka, India.

56. Kumar SN, Fred AL, Varghese PS. 2018. An overview of segmentation algorithms for the analysis of anomalies on medical images. *J Intell Syst* 29(1): 612-625. https://doi.org/10.1515/jisys-2017-0629

57. Biratu ES, Schwenker F, Debelee TG, Kebede SR, Negera WG, et al. 2021. Enhanced region growing for brain tumor MR image segmentation. *J Imaging* 7(2): 22. https://doi.org/10.3390/jimaging7020022

58. Bougacha A, Boughariou J, Slima MB, Hamida AB, Mahfoudh KB, et al. 2018. Comparative study of supervised and unsupervised classifica-

tion methods: application to automatic MRI glioma brain tumors segmentation. In 4th International Conference on Advanced Technologies for Signal and Image Processing, Sousse, Tunisia.

59. Ma C, Luo G, Wang K. 2018. Concatenated and connected random forests with multiscale patch driven active contour model for automated brain tumor segmentation of MR images. *IEEE Trans Med Imaging* 37(8): 1943-1954. https://doi.org/10.1109/TMI.2018.2805821
60. Fülöp T, Győrfi Á, Csaholczi S, Kovács L, Szilágyi L. 2020. Brain tumor segmentation from multi-spectral MRI data using cascaded ensemble learning. In IEEE 15th International Conference of System of Systems Engineering, Budapest, Hungary.
61. Ale Y, Nainwal N. 2023. Progress and challenges in the diagnosis and treatment of brain cancer using nanotechnology. *Mol Pharm* 20(10): 4893-4921. https://doi.org/10.1021/acs.molpharmaceut.3c00554
62. Shabani L, Abbasi M, Amini M, Amani AM, Vaez A. 2022. The brilliance of nanoscience over cancer therapy: novel promising nanotechnology-based methods for eradicating glioblastoma. *J Neurol Sci* 440: 120316. https://doi.org/10.1016/j.jns.2022.120316