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A Comprehensive Study on Classification of Brain Tumor Detection by using Machine Learning

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Abstract
Cells develop quickly and uncontrollably, which causes brain tumours.It may cause death if not addressed in the beginning stages.Although there have been many substantial efforts and encouraging results in this field, precise segmentation and classification remain difficult tasks.Because of the differences in tumour location, shape, and size, detecting brain tumours is extremely difficult.The goal of this survey is to provide researchers with a thorough literature review on brain tumour detection using magnetic resonance imaging.The anatomy of brain tumours, datasets that were made available to the public, augmentation methods, segmentation, feature extraction, classification, and deep learning, transfer learning, and quantum machine learning for the study of brain tumours were all included in this survey.Finally, this review presents all relevant material for the detection of brain tumours, including its benefits, drawbacks, advances, and outlook.

keywords: Brain imaging modalities, segmentation, feature extraction, MRI, and stroke are some related

Introduction
The classification of brain tumors—and thus the choice of optimal treatment options—can become more accurate and precise through the use of artificial intelligence in combination with physiological imaging. This is the result of an extensive study published in Cancers and conducted by the Karl Landsteiner University for Health Sciences (KL Krems). Multiclass machine learning methods were used to analyze and classify brain tumors using physiological data from magnetic resonance imaging. The results were then compared with classifications made by human experts. Artificial intelligence was found to be superior in the areas of accuracy, precision and misclassification, among others, while professionals performed better in sensitivity and specificity.
Brain tumors can be easily detected by magnetic resonance imaging (MRI), but their exact classification is difficult. Yet that's precisely what's crucial for choosing the best possible treatment options. Now, an international team led by KL Krems has used data from modern MRI methods as the basis for machine learning (ML) protocols and assessed the use of artificial intelligence to classify brain tumors. They found that in certain areas, classification using artificial intelligence can be superior to that performed by trained professionals.

More MRI, more data
The team led by Prof. Andreas Stadlbauer, a scientist at the Central Institute for Medical Radiology Diagnostics at St. Pölten University Hospital, used both advanced and physiological MRI data for the study. Both methods provide enhanced insight into the structure and metabolism of a brain tumor and have allowed better classification for some time. But the price to pay for such a differentiated picture is enormous amounts of data that need to be expertly assessed. "We have now analyzed whether and how an artificial intelligence using ML can be enabled to support trained professionals in this Herculean task," explains Prof. Stadlbauer. "And the results are very promising. When it comes to accuracy, precision and avoiding misclassification, an AI can classify brain tumors well using MRI data."
To achieve their impressive result, the team trained nine well-known Multiclass ML algorithms with MRI data from 167 previous patients who had one of the five most common brain tumors and had accurate classification using histology. A total of 135 so-called classifiers were generated in a complex protocol. These are mathematical functions that assign the material to be examined to specific categories. "In contrast to previous

studies, we also took into account data from physiological MRIs," explains Prof. Stadlbauer. "This included details on the vascular architecture of the tumors and their formation of new vessels, as well as the supply of oxygen to the tumor tissue."

Radiophysionomics

The team named the combination of data from different MRI methods with multiclass ML "radiophysiomics." It's a term that's likely to catch on quickly, as the potential of this approach became apparent in the second part of the project, the testing phase. In this, the now-trained multiclass ML algorithms were fed with corresponding MRI data from 20 current brain tumor patients and the results of the classifications thus obtained were compared with those of two certified radiologists. Thereby, the two best ML algorithms (referred to as "adaptive boosting" and "random forest"), outperformed the human assessment results in the areas of accuracy and precision. Also, these ML algorithms resulted in less misclassification than by the professionals (5 versus 6). On the other hand, when it came to the sensitivity and specificity of the assessment, the human assessments proved to be more accurate than the AI tested.

"This also makes it clear," says Prof. Stadlbauer, "that the ML approach should not be a substitute for classification by qualified personnel, but rather a supplement to it. In addition, the time and effort required for this approach is currently still very high. But it offers a possibility whose potential should be further pursued for everyday clinical use." Overall, this study again demonstrates the focus of research at KL Krems on fundamental findings with real clinical added value.

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Improving Brain Tumor Segmentation at the Edge

Intel's Abhishek Khowala, principal health AI engineer, and SéverineHabert, AI engineering manager, discuss some of the enhancements in brain tumor segmentation for enabling diagnosis.

While most brain tumors are benign, early detection is critical for the best treatment options and outcomes. Assessing a diagnosis starts with MRI 2D and 3D imaging. Segmentation of the brain tumor – or separating the tumor from normal brain tissues – is essential to identifying three key factors to allow doctors to move forward:

- Is the tumor benign or malignant?
- The approximate tumor size and location.
- Plan out the treatment options.

"We need to segment out the tumor from the rest of the tissues around it," Khowala says. "For that, there is the unit model. And that architecture works with fewer amounts of data yet provides a clearer segmentation result."

The brain tumor segmentation (BraTS) combined with OpenVINO™ toolkit could optimize MRI results during tumor detection and monitoring. "Since this is something that has to happen worldwide, we need to deploy it at scale," Khowala explains. Scaling requires overcoming a few challenges. Utilizing OpenVINO erases issues of high-cost GPU required for deploying AI solutions or perceived performance limitations of common frameworks such as PyTorch or TensorFlow. "Brain tumor segmentation is a perfect example of applying the most common architecture and using it for multiple devices from edge to handheld devices," Habert adds.

For optimized AI, the provided data must be robust, which is not an easy task. According to Khowala, Expert radiologists are required to interpret the MRI images to get to the ground truth data. BraTS helps predict results and compare accuracy with provided ground truth results using the Sørensen–Dice coefficient datasets. Once the data is available, modeling can take place and assist medical professionals in their diagnosis.

Machine learning can predict cerebral palsy, study says

A new machine learning tool could predict cases of cerebral palsy in young infants with brain damage, according to a July 11 international study published in JAMA Network Open.

The study looked at more than 500 infants with a high risk of perinatal brain damage at hospitals across the U.S., Belgium, India and Norway using video recordings of their movements. Of these videos, 75 percent went through a deep learning algorithm analysis for predicting cerebral palsy and 25 percent of them went through an external validation process using medical professionals.

The results revealed that the machine learning algorithm had a sensitivity of 71.4 percent, meaning it predicted true cases at that rate. It also had a specificity of 94.1 percent, indicating that the model correctly predicts almost all negative cases. The authors concluded that "this study's findings suggest that deep learning–based assessments could support early detection of CP in infants at high risk."

Literature Survey

The body's sensory information and associated actions are distributed throughout it by the central nervous system [1-3].This dissemination is aided by the spinal cord and the brain.The brain stem, cerebrum, and

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cerebellum are the three major components of the brain [4].A typical male human brain weighs between 1.2 and 1.4 K and has a volume of 1260 cm3 for men and 1130 cm3 for women [5].The frontal lobe of the brain aids in decision-making, motor control, and problem-solving. Body position is controlled by the parietal lobe.The temporal lobe regulates hearing and memory processes, whereas the occipital lobe is in charge of the brain's visual processing.

The cerebral cortex, a material that is greyish and located on the outside of the brain, is made up of cortical neurons [6]. In comparison to the cerebrum, the cerebellum is relatively smaller. It is in charge of motor control, which is the systematic management of free will in living things with nerve systems. The little lesion zone cannot be detected by ALI, lesionGnb, or LINDA techniques because of the fluctuating size and stroke territory. Humans have a well-developed and well-structured cerebellum compared to other species [7]. There are three lobes in the cerebellum: an anterior, a posterior, and a flocculonodular lobe. The vermis, a spherical structure, joins the anterior and posterior lobes.

The cerebellum is made up of an outer grey cortex that is slightly thinner than the cerebrum and an inner region of white matter (WM). The coordination of complicated motor motions is aided by the anterior and posterior lobes. Balance in the body is maintained by the flocculonodular lobe [4, 8]. The brain stem is a 7–10 cm-long stem-like structure, as its name suggests. It contains bundles of cranial and peripheral nerves that help with breathing and other vital functions like eye movement and regulation, balance, and maintenance.

The brain stem is the final stop on the neural pathways leading from the thalamus of the cerebrum to the spinal cord. They then spread all over the body after that. The medulla, pons, and midbrain make up the majority of the brain stem.The midbrain helps with functions like processing motor, auditory, and visual information as well as controlling eye movements. The medulla oblongata aids in blood control, swallowing, sneezing, and other bodily functions, while the pons aids in breathing, intra-brain communication, and feelings [9].

Brain tumor and stroke

Brain tumours are categorised as either aggressive or slow-growing [2, 10–20]. A malignant (aggressive) tumour spreads from an initial site to a secondary site, whereas a benign (slow-growing) tumour does not penetrate the surrounding tissues [16, 17, 21–27]. Grades I through IV of a brain tumour are described by the WHO. Tumors of grades I and II are thought to grow slowly, whereas those of grades III and IV are more aggressive and have a worse prognosis [28]. The specifics of brain tumour grading are as follows in this regard:

I cancers develop gradually and do not spread quickly. These can nearly entirely be removed through surgery and are linked to greater long-term survival chances. Grade 1 pilocyticastrocytoma is an illustration of one such tumour.

II: These tumours have a similar slow growth rate but have the potential to spread to nearby tissues and progress to higher grades. Even after surgery, these tumours are prone to recurrence. An example of one of these tumours is the oligodendroglioma.

III: These tumours can penetrate the surrounding tissues and grow more quickly than grade II cancers. Such tumours require post-surgical radiation or chemotherapy as surgery alone is ineffective in treating them. Anaplastic astrocytoma is an illustration of one such tumour.

IV: The most aggressive and easily disseminated cancers fall into this category. They might even exploit blood vessels to develop quickly. Such a tumour is the glioblastoma multiforme [29].

Ischemic stroke: An aggressive brain illness, ischemic stroke is a leading cause of disability and death worldwide [30]. When the blood supply to the brain is cut off, underperfusion (leading in tissue hypoxia) and the death of the advanced tissues in hours are the symptoms of an ischemic stroke [31]. Stroke lesions are classified as acute (0–24 h), subacute (24–2 weeks), or chronic (> 2 weeks) depending on their severity [32].

The structure of the brain can be examined using three main techniques (PET, CT, DWI, and MRI) for brain malignancies.

Positron emission tomography

A unique class of radioactive tracers is used in positron emission tomography (PET). PET is used to examine the metabolic characteristics of brain tumours, including blood flow, glucose metabolism, lipid synthesis, oxygen consumption, and amino acid metabolism. It is still regarded as one of the most effective metabolic procedures and makes use of fluorodeoxyglucose (FDG), one of the best nuclear medicine agents [33]. FDG is a popular PET tracer that is utilised in brain imaging. FDG-PET images do, however, have several drawbacks, such as the difficulty to distinguish between necrosis radiation and a recurring high-grade (HG) tumour [34]. Additionally, radioactive tracers used in PET scans can injure a person's body and result in an allergic reaction after the scan. Iodine and aspartame allergies can occur in patients. Furthermore, due to their inferior spatial resolution when compared to an MRI scan, PET tracers do not provide reliable localization of anatomical structure [35].

Computed tomography

Compared to images produced by standard X-rays, computed tomography (CT) images offer more detailed information. Since its debut, the CT scan has garnered widespread endorsement and adoption. According to a study [36], there are 62 million CT scans performed annually in the USA alone, of which 4 million are performed on children. The soft tissues, blood arteries, and bones of many human body components are visible

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on CT scans. As opposed to standard X-rays, it employs more radiation. Multiple CT scans may expose you to more radiation, which could increase your chance of developing cancer. According to CT radiation exposures, the risks of developing cancer have been calculated [37, 38]. High contrast between the soft tissues in MRI allows for a clearer anatomical view of features that are obscured in a CT scan.

Magnetic resonance imaging

An MRI scan is utilised to thoroughly examine various body regions and also aids in the early detection of brain disorders than other imaging modalities [40]. As a result, tumour segmentation is a difficult task due to the complexity of brain structures [41–47]. This review includes feature extraction and reduction techniques, segmentation techniques, classification techniques, and deep learning strategies. Finally, performance metrics and benchmark datasets are supplied.

Diffusion weighting imaging

Based on a number of factors, including age, location, and extent regions, MRI sequences are used to assess the stroke lesions [50]. A computerised method may be used for reliable diagnosis of the illness development rate in the context of treatment [51]. The cognitive neuroscientists, who commonly do studies linking cerebral dysfunction to cognitive function

They found that analysing the entire infected region of the brain to aid in the therapy process requires segmentation of the stroke lesions [52]. Segmenting stroke lesions is a challenging task, though, as the appearance of strokes changes over time. For the purpose of identifying stroke lesions, the MRI sequences Diffusion Weighted Imaging (DWI) and FLAIR are used.

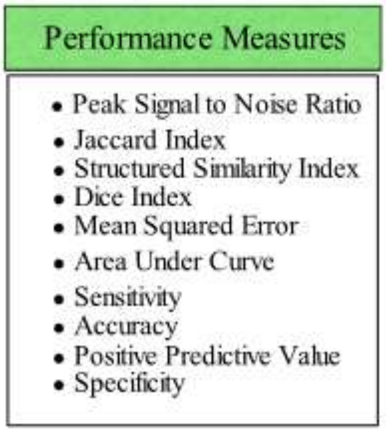
The infection component is highlighted as a hyperintensity in the acute stoke stage DWI sequence. The under-perfusion zone is a representation of the perfusion's mapping magnitude [53]. Two regions' differences could be thought of as penumbra tissue. The locations and shapes of stroke lesions vary. It is possible for multiple lesions to form at the same time and come in a variety of sizes and shapes. These lesions are also not matched with vascular patterns.

The stroke lesions are a complete hemisphere in size and have radii of a few millimetres. Due to the different hemisphere's structure, the infection's strength may vary greatly within the affected area. Additionally, as chronic stroke lesions and white matter hyperintensities have a similar appearance to each other, automated stroke segmentation is challenging [54].

Evaluation and validation

In the literature now in existence, experimental findings are assessed against publically accessible datasets to confirm the robustness of algorithms.

A number of publicly accessible datasets are used by the researchers to assess the suggested techniques. This section talks about several significant and difficult datasets. The most difficult MRI datasets are BRATS [55–57]. More challenges in the BRATS Challenge with a resolution of 1 mm 3 voxels are published in different years. Both Fig. 1 and Table 1 provide the datasets' details.



Performance measures for Brain Tumour

The effectiveness of the method is mostly determined by the performance metrics. Fig. 2 presents a set of performance metrics.

Preprocessing is an important step [61] in order to extract the necessary region. The removal of non-brain tissue is accomplished using the 2D brain extraction algorithm (BEA) [62], the FMRIB software library [63], and BSE [64], as illustrated in Fig. 3. Due to the radio frequency coil's flaws, known as intensity inhomogeneity, the bias field is a major issue in MRI [65, 66]. It has been fixed as depicted in Fig. 4 [67]. Different situations [69-72] call for the adoption of preprocessing techniques including linear, nonlinear [68], fixed, multi-scale, and pixel-based. Direct image analysis is frequently made difficult by the minute differences between normal and diseased tissues caused by noise [68] and artefacts [73, 74]. Brain tumour segmentation is done using AFINITI [63]. As a

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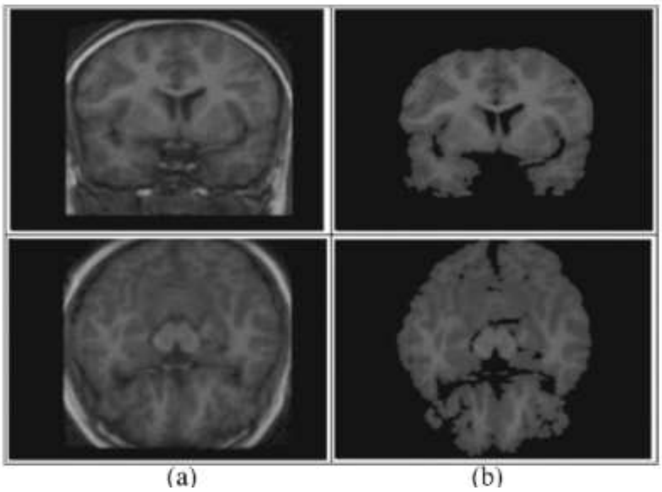
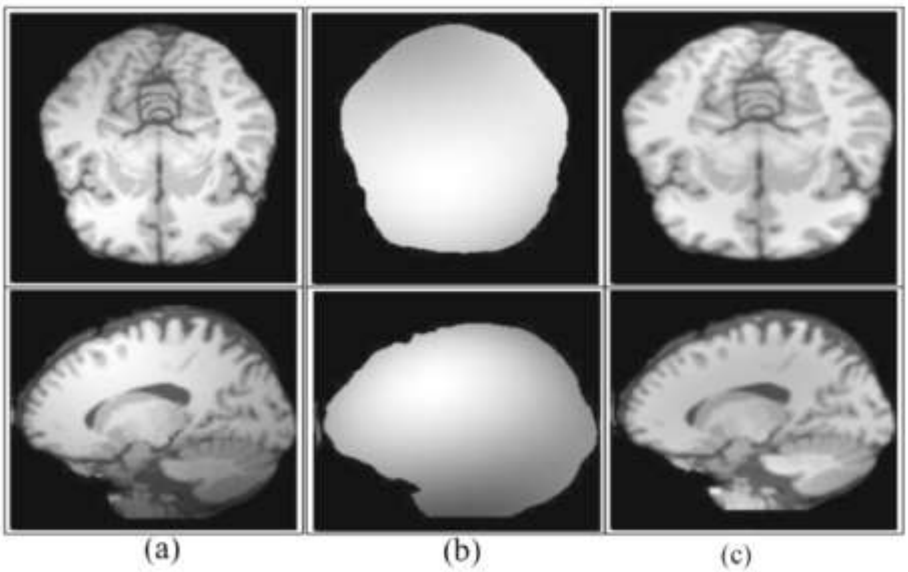
result, automated procedures are used, where segmentation is handled by computer software, negating the necessity for manual human contact [75, 76]. There is a lot of use of fully and partially automated procedures [77, 78]. Table 2 lists the outcomes of the segmentation of brain tumours. The segmentation techniques are separated into the following groups:



Skull remover (a) input (b) skull removed

Due to its slow processing speed, an anisotropic diffusion filter is more appropriate in real-world applications [97, 98]. It is challenging to restore the edges when the image's noise level is high [99]. Another step in the preprocessing procedure is to normalise the image's intensity [2, 100, 101]; this is done using the modified curvature diffusion equation (MCDE) [102]. Medical imaging uses the Wiener filter to improve the local and spatial information [103]. N4ITK [104] for bias field correction, the median filter [104] for picture smoothing, the anisotropic diffusion filter [105], image registration [106], sharpening [107], and skull stripping using the brain extraction tool (BET) [108] are some of the popular preprocessing techniques.



Bias field correction a input, b estimated, c corrected

Segmentation

From input photos, segmentation extracts the necessary region. Therefore, accurately segmenting lesion sites is a more important endeavour [109]. Semi- and completely automated approaches are used [46] since the manual segmentation procedure is flawed [110]. Semi-automated segmentation techniques outperform manual segmentation in terms of accuracy [111, 112]. Initialization, evaluation, and feedback reaction are the other divisions made into semi-automated procedures [113, 114].

The thresholding method is a straightforward and effective way to segment the necessary items [18], but choosing an optimum threshold in low-contrast images might be challenging.

Based on image intensity, threshold values are chosen using histogram analysis [115]. There are two types of thresholding techniques: local and global. The global thresholding method is the best choice for segmentation when the objects and background have a high degree of uniform contrast or intensity.

The Gaussian distribution approach can be used to find the ideal threshold value [116]. These techniques are used when the threshold value cannot be determined from the entire image histogram or when a single threshold value does not produce satisfactory segmentation results [117]. The thresholding method is typically used as the initial stage of segmentation, and the gray-level images are separated into numerous unique regions as illustrated in Fig..

In RG methods, nearby pixels are combined with homogeneousness features based on predefined similarity criteria to analyse image pixels from discontinuous locations. Due to the partial volume effect, region expansion may fall short of offering higher precision [118, 119].

MRGM is preferred to counteract this impact [86, 120]. Also introduced is the region developing using BA approaches [87].

Watershed methods are used to examine the intensity of the picture because MR images have a higher intensity of proteinaceous fluid [114, 121, 122]. The watershed approach causes over-segmentation [124] because of noise [123]. When watershed transform and statistical methods are combined [126, 127], accurate segmentation [125] results can be produced. Topological watershed [128], image foresting transform (IFT) watershed [129], and marker-based watershed [130] are a few examples of watershed algorithms.

There is potential for improvement, according to the thorough literature assessment [131] on brain tumour detection [72]. Existing tumour segmentation techniques need to be improved since brain tumours come in a variety of sizes and shapes. Enhancement [132–134] and segmentation [135–137] are important in tumour identification for overcoming the limits of existing approaches.

Feature extraction methods

The feature extraction techniques [12, 138–140] include GLCM [15, 141, 142], geometrical features (area, perimeter, and circularity) [15], first-order statistical (FOS), GWT [143, 144], Hu moment invariants (HMI) [145], multifractal features [146], 3D Haralick features [147], LBP [148], GWT [11], HOG [14, 137], texture and shape [82, 143,The summary of feature extraction techniques is shown in Table 3.

High-dimensional features boost system execution time and memory demand for processing in machine learning and computer vision applications. As a result, in order to distinguish between essential and irrelevant features, a variety of feature selection techniques are needed [168]. The best feature extraction still presents a difficult problem [47]. To eliminate redundant features, one can use the single-point heuristic search method, ILS, genetic algorithm (GA), GA+ fuzzy rough set, hybrid wrapper-filter, TRSFFQR, tolerance rough set (TRS), firefly algorithm (FA), Kullback-Leibler divergence measure, iterative sparse representation, recursive feature elimination (RFE), CSO-SIFT, entropy, PCA, and LDA.

A list of classification techniques is provided in Table 4.

The input data are categorised using classification algorithms, and training and testing are carried out on known and unknown samples [16, 24, 25, 181–192]. Machine learning is frequently used to classify tumours into the proper groups, including benign and malignant tumour [15, 47, 163, 194, 195], tumour and non-tumor [26], and tumour substructure (complete/non-enhanced/enhanced) [193]. While FCM [197, 198], hidden Markova random field [199], self-organizing map [101], and SSAE [200] are unsupervised techniques, KNN [196], SVM, closest subspace classifier, and representation classifier [143] are supervised techniques.

Brain tumor detection using transfer learning

Due to the asymmetrical lesions' shape, geographical flexibility, and hazy margins, manual identification of brain tumours is challenging. Consequently, a transfer-learning model based on the super-pixel has been proposed. The VGG-19 is a pre-trained model that has been used to categorise the various glioma grades, such as high/low glioma. On the 2019 series of brats, the approach scored 0.99 AUC[232]. On the brain datasets, the three separate pre-trained models—VGG network, Google network, and Alex network—are used to classify gliomas, pituitary tumours, and meningiomas.

In this technique, MRI slices are also subjected to augmentation methods in order to generalise the results and alleviate the overfitting issue by boosting the amount of input data.

We conclude that VGG-16 offers better than 98 percent classification accuracy after conducting experimental analysis utilising several pre-trained models [233]. In order to classify the many types of brain tumour, such as gliomas, pituitary I tumours, and meningiomas, two different types of networks—the visual attention network and CNN—have been used [234]. For the investigation of brain tumours, the VGG-16, Alex, and Google net pre-trained models are studied.

To increase the visual contrast, input slices have been processed using frequency domain techniques. The following process involves passing the photos with increased contrast. Pre-trained VGG-16 yields the best classification results in these cases [235]. For the detection of brain cancers, the Laplacian filter with a multi-layered dictionary model is used. When compared to earlier efforts, the model performed better [236]. Pre-

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processing, data augmentation, and segmentation and classification utilising transfer learning models are the three main components of the procedure.

Brain tumor detection using quantum machine learning

Entanglement, parallelism, and superposition of quantum states can all be utilised to prove the superiority of quantum computers [258].Due to a lack of computing power for running quantum algorithms, investigating the entanglement of quantum characteristics for efficient computation is a challenging endeavour.Classical computers built on quantum theory and impacted by qubits are no longer able to fully take advantage of the advantages of quantum state and entanglement as a result of advances in quantum techniques.Due to the inherent qualities provided by quantum physics, QANN has been demonstrated to be efficient in a range of computer tasks, including classification and pattern recognition [259]. Quantum models based on genuine quantum computers, on the other hand, use big bits of the quantum/qubits as a simple representation of matrix and linear functions. However, due to the complicated and time-consuming back-propagation quantum model, the computational complexity of quantum-inspired neural network (QINN) designs increases several fold [260]. The automatic segmentation of brain lesions from MRI, which eliminates the onerous manual work of human specialists or radiologists, greatly aids in the detection of brain tumours. On the other hand, manual brain tumour diagnosis suffers from large variations in size, shape, orientation, illumination variations, greyish overlaying, and cross-heterogeneity.

The current study focuses on a novel quantum fully supervised learning process defined by qutrits for the timely and effective segmentation of lesions. The main goal of the proposed work is to accelerate the QFS-convergence Nets and make them suitable for computerised segmentation of brain lesions without the need for any learning/supervision. To take advantage of the properties of quantum correlation, a quantum fully self-supervised neural network (QFS-Net) model was proposed that uses qutrits/three states of quantum for segmentation of brain lesions [261]. The QFS-Net replaces the sophisticated quantum back-propagation method used in supervised QINN networks with a revolutionary fully supervised qutrit-based counter propagation method.

Recent literature on the detection of brain tumours is reviewed in this survey, and it is concluded that there is still room for improvement. MRI includes noise during image acquisition, and noise removal is a difficult task [2, 262-264]. Because brain tumours have tentacles and diffused structures, accurate segmentation is difficult [265]. Selecting and extracting optimal features, as well as the appropriate number of training/testing samples, is an important task for better classification [191, 192].

Deep learning models are gaining popularity because they automate feature learning; however, they require a lot of computing power and memory. As a result, there is still a need to develop a lightweight model that provides high ACC in a short amount of computational time. Table 7 lists some existing machine learning methods and their limitations. The tumours of glioma and stroke are not well contrasted. It has tentacle and diffused structures that make segmentation and classification more difficult [270]. A small volume of tumour detection remains difficult because it can be mistaken for a normal region [269, 273].

Conclusion

Because of tumour appearance, variable size, shape, and structure, accurate brain tumour detection remains difficult. Although tumour segmentation methods have shown great promise in analysing and detecting tumours in MR images, much more work is needed to accurately segment and classify the tumour region. Existing work has limitations and challenges in identifying tumour substructures and classifying healthy and unhealthy images. In summary, this survey covers all important aspects and the most recent work done to date, as well as their limitations and challenges. It will aid researchers in developing an understanding of how to conduct new research in a timely and effective manner. Deep learning methods have made significant contributions, but a generic technique is still required. When training and testing are performed on similar acquisition characteristics (intensity range and resolution), these methods produce better results; however, a slight variation in the training and testing images directly affects the robustness of the methods. Future research can be done to detect brain tumours more accurately, using real patient data from any medium (different image acquisition methods) (scanners). Handcrafted and deep features can be combined to improve classification outcomes. Similarly, lightweight methods such as quantum machine learning play an important role in improving accuracy and efficacy, saving radiologists' time and increasing patient survival rates.

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