



A Comprehensive Systematic Review of MRI Techniques for the Early Detection of Brain Tumors: Clinical Implications and Diagnostic Accuracy

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ABSTRACT

Background: Brain tumours are malignancies of brain tissues. Characterising such tissues and identifying related genes can help to estimate tumour spread, and further help to identify tumour grades for the treatment planning. Such characterisation comprises of the different tumour components assessment. **The aim:** The aim of this study to show about MRI techniques for the early detection of brain tumors. **Methods:** By the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) 2020, this study was able to show that it met all of the requirements. **Result:** Eight publications were found to be directly related to our ongoing systematic examination after a rigorous three-level screening approach. Subsequently, a comprehensive analysis of the complete text was conducted, and additional scrutiny was given to these articles. **Conclusion:** MRI plays a major role in the diagnosis, grading, treatment and treatment response assessment of brain tumours and other intracranial lesions. Several adjunct MR imaging techniques have been developed to quantitatively measure a number of biophysical properties of brain tissue in vivo, allowing regional changes in the tissue microstructural environment to be better characterised. These techniques include diffusion-weighted imaging (DWI), perfusion-weighted imaging (PWI) and magnetic resonance spectroscopy (MRS).

Keyword: Brain tumor, detection, diagnostic, imaging, MRI techniques.

INTRODUCTION

A brain tumor is an abnormal mass of tissues that grows and multiplies rapidly. It can originate within the brain, which is called primary brain tumor, or in other surrounding areas and moves to the brain at a later stage, which is called metastatic brain tumor. There are more than 120 types of tumors classified as benign or malignant (cancerous). Cancerous tumors cause serious health problems such as severe headaches, blindness, and paralysis. The timely detection and diagnosis of these tumors at their very early stages help clinicians to decide the most appropriate treatment protocol.^{1,2}

Magnetic resonance imaging (MRI) is one of the most advanced medical imaging modalities. It is a noninvasive soft tissue contrast imaging used for the diagnosis of tumors within the human brain tissues. MRI system produces image scans through the application of a combination of radio waves and a strong magnetic field to align the

magnetic spins in body organs along the magnetic field. When the radio frequency is turned off, the spin system produces a signal, called the free induction decay (FID) signal, which reflects the water content of brain tissues. The FID signal is processed further to give a two dimensional (2D) image of the organ tissues. MRI systems are capable of producing images of different sections (slices) within the brain with no overlap of other anatomical structures, which can provide detailed information about brain tumors such as exact location, shape, and size. This information can help clinicians and surgeons to reach an accurate diagnosis of tumors in order to determine the appropriate treatment procedure/protocol such as surgery, chemotherapy, and radiotherapy.^{1,3}

Artificial intelligence (AI) plays a significant role in the detection and diagnosis of brain tumors, making it a useful complement to the notoriously difficult field of brain tumor surgery. Subsets of artificial intelligence like

machine learning (ML) and deep learning (DL) have revolutionized neuropathological practices. Preprocessing of data, feature extraction, feature selection, feature reduction, and classification are only a few of the steps involved in these methods. According to ref., AI has helped boost neuropathologist's assurance in making diagnoses of brain tumors, allowing them to make better decisions for their patients.^{4,5}

Recent developments in deep learning have led to a wide range of useful applications in fields as disparate as pattern classification, object detection, voice recognition, and decision making. Researchers in the healthcare industry have used a variety of ML algorithms, such as support vector machines (SVMs), k-nearest neighbor (k-NN), decision trees, Naive Bayes, and DL algorithms, such as trained convolutional neural networks (CNNs), VGGNets, GoogleNet, and ResNets, to aid in the diagnosis of cancer. In addition, research development is hampered by the dearth of comprehensive medical datasets due to privacy issues that

prevent the exchange in patient information. In addition, because existing methods lack precision and recall, they are inefficient and take too long to classify images, which can postpone the start of treatment. It can be used to diagnose neurological diseases and analyze images of brain tumor cancer.^{4,6,7}

It is crucial to accurately identify the type of brain disorder to reduce diagnostic errors. Utilizing computer-aided diagnostic (CAD) technologies can improve accuracy. The fundamental idea behind CAD is to offer a computer result as an additional guide to help radiologists interpret images and shorten the reading time for images. This enhances the accuracy and stability of radiological diagnosis. Several CAT-based artificial intelligence techniques, such as machine learning (ML) and deep learning (DL), are described in this review for diagnosing tissues and segmenting tumors. The segmentation process is a crucial aspect of image processing. This approach includes a procedure for extracting the area that helps determine whether a region is

infected. Using MRI images to segment brain tumors presents various challenges, including image noise, low contrast, loss borders, shifting intensities inside tissues, and tissue-type variation. The most complex and crucial task in many medical image applications is detecting and segmenting brain tumors because it often requires much data and information. Tumors come in a variety of shapes and sizes. Automatic or semiautomatic detection/segmentation, helped by AI, is currently crucial in medical diagnostics.^{8,9}

METHODS

Protocol

By following the rules provided by Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) 2020, the author of this study made certain that it was up to par with the requirements. This is done to ensure that the conclusions drawn from the inquiry are accurate.

Criteria for Eligibility

For the purpose of this literature review, we compare and contrast MRI techniques for the early detection of

brain tumors. It is possible to accomplish this by researching of the MRI techniques for the early detection of brain tumors. As the primary purpose of this piece of writing, demonstrating the relevance of the difficulties that have been identified will take place throughout its entirety.

In order for researchers to take part in the study, it was necessary for them to fulfil the following requirements: 1) The paper needs to be written in English, and it needs to determine about the MRI techniques for the early detection of brain tumors. In order for the manuscript to be considered for publication, it needs to meet both of these requirements. 2) The studied papers include several that were published after 2014, but before the time period that this systematic review deems to be relevant. Examples of studies that are not permitted include editorials, submissions that do not have a DOI, review articles that have already been published, and entries that are essentially identical to journal papers that have already been published.

Search Strategy

We used "MRI techniques for the early detection of brain tumors." as keywords. The search for studies to be included in the systematic review was carried out using the PubMed, SagePub, and Sciencedirect databases.

Data retrieval

After reading the abstract and the title of each study, the writers performed an examination to determine whether or not the study satisfied the inclusion criteria. The writers then decided which previous research they wanted to utilise as sources for their article and selected those studies. After looking at a number of different research, which all seemed to point to the same trend, this conclusion was drawn. All submissions need to be written in English and cannot have been seen anywhere else.

Only those papers that were able to satisfy all of the inclusion criteria were taken into consideration for the systematic review. This reduces the number of results to only those that are pertinent to the search. We do not take into consideration the conclusions of any study that does not

satisfy our requirements. After this, the findings of the research will be analysed in great detail. The following pieces of information were uncovered as a result of the inquiry that was carried out for the purpose of this study: names, authors, publication dates, location, study activities, and parameters.

Quality Assessment and Data Synthesis

Each author did their own study on the research that was included in the publication's title and abstract before making a decision about which publications to explore further. The next step will be to evaluate all of the articles that are suitable for inclusion in the review because they match the criteria set forth for that purpose in the review. After that, we'll determine which articles to include in the review depending on the findings that we've uncovered. This criteria is utilised in the process of selecting papers for further assessment. in order to simplify the process as much as feasible when selecting papers to evaluate. Which earlier investigations were carried out, and what elements of those studies made it appropriate to

include them in the review, are being discussed here.

Table 1. Search Strategy

<i>Database</i>	<i>Search Strategy</i>	<i>Hits</i>
Pubmed	((("Tumor"[MeSH Subheading] OR "Brain tumor"[All Fields] OR "Diagnosed" [All Fields]) AND ("Diagnostic"[All Fields] OR "Imaging"[All Fields]) AND ("Techniques"[All Fields]) OR ("Detection" [All Fields]))	2610
Science Direct	((("Tumor"[MeSH Subheading] OR "Brain tumor"[All Fields] OR "Diagnosed" [All Fields]) AND ("Diagnostic"[All Fields] OR "Imaging"[All Fields]) AND ("Techniques"[All Fields]) OR ("Detection" [All Fields]))	1490
Sagepub	((("Tumor"[MeSH Subheading] OR "Brain tumor"[All Fields] OR "Diagnosed" [All Fields]) AND ("Diagnostic"[All Fields] OR "Imaging"[All Fields]) AND ("Techniques"[All Fields]) OR ("Detection" [All Fields]))	0
		566

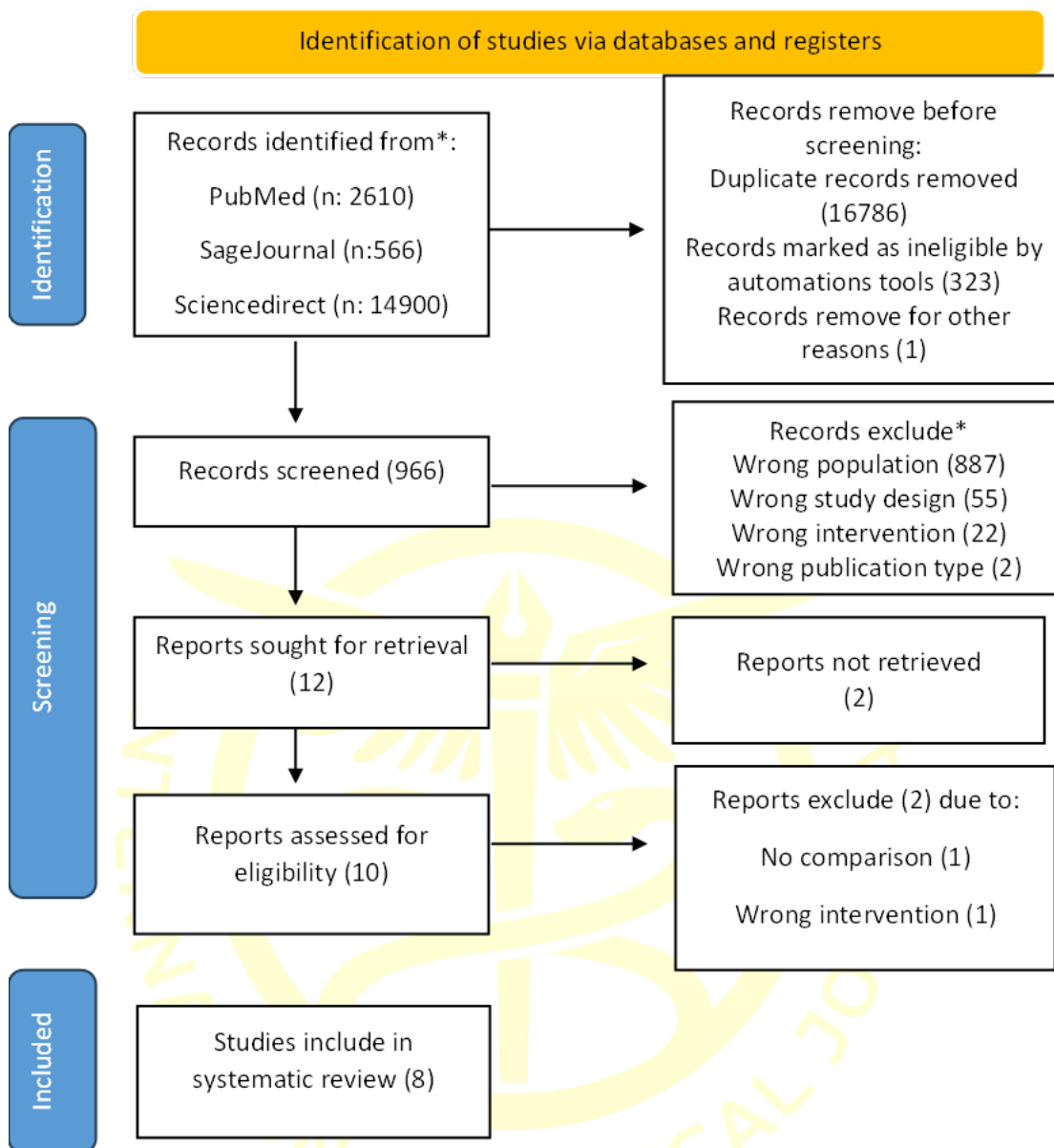


Figure 1. Article search flowchart

Table 2. Critical appraisal of Study

Parameters	(Saeedi, S et al., 2023)	(Aggarwal, M et al., 2023)	(Isaza, AA et al., 2023)	(Taheer, F et al., 2022)	(Khan, MSI et al., 2022)	(Maqsood, S et al., 2022)	(Gao, P et al., 2022)	(Mahmud, MI et al., 2023)
1. Bias related to temporal precedence								
Is it clear in the study what is the “cause” and what is the “effect” (ie, there is no confusion about which variable comes first)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2. Bias related to selection and allocation								
Was there a control group?	No	No	No	No	No	No	No	No
3. Bias related to confounding factors								
Were participants included in any comparisons similar?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
4. Bias related to administration of intervention/exposure								
Were the participants included in any comparisons receiving similar treatment/care, other than the exposure or intervention of interest?	No	No	No	No	No	No	No	No
5. Bias related to assessment, detection, and measurement of the outcome								
Were there multiple measurements of the outcome, both pre and post the intervention/exposure?	No	No	No	No	No	No	No	No
Were the outcomes of participants included in any comparisons measured in the same way?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Were outcomes measured in a reliable way?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6. Bias related to participant retention								
Was follow-up complete and, if not, were differences between groups in terms of their follow-up adequately described and analyzed?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
7. Statistical conclusion validity								
Was appropriate statistical analysis used?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

RESULT

Using reputable resources like Science Direct, PubMed, and SagePub, our research team first gathered 18076 publications. A thorough three-level screening strategy was used to identify only eight papers as directly relevant to our ongoing systematic evaluation. Next, a thorough study of the entire text and further examination of these articles were selected. Table 3 compiles the literature that was analyzed for this analysis in order to make it easier to view.

Table 3. The literature include in this study

Author	Origin	Method	Result
Saeedi, S et al., 2023 ¹⁰	Iran	A dataset containing 3264 Magnetic Resonance Imaging (MRI) brain images comprising images of glioma, meningioma, pituitary gland tumors, and healthy brains were used in this study. First, preprocessing and augmentation algorithms were applied to MRI brain images.	The training accuracy of the proposed 2D CNN and that of the proposed auto-encoder network were found to be 96.47% and 95.63%, respectively. The average recall values for the 2D CNN and auto-encoder networks were 95% and 94%, respectively. The areas under the ROC curve for both networks were 0.99 or 1. Among applied machine learning methods, Multilayer Perceptron (MLP) (28%) and K-Nearest Neighbors (KNN) (86%) achieved the lowest and highest accuracy rates, respectively. Statistical tests showed a significant difference between the means of the two methods developed in this study and several machine learning methods (p -value < 0.05).
Aggarwal, M et al., 2023 ¹¹	India	To overcome the gradient issue of DNN, this research work provides an efficient method for brain Tumor segmentation based on the Improved Residual Network (ResNet). Existing ResNet can be improved by maintaining the	The proposed improved Resnet address all three main components of existing ResNet: the flow of information through the network layers, the residual building block, and the projection shortcut. This approach minimizes computational costs and speeds up the process.

		details of all the available connection links or by improving projection shortcuts.	
Isaza, AA et al., 2023¹²	Colombia	We focused on the classification of three types of tumors: glioma, meningioma, and pituitary. With the Figshare brain tumor dataset was trained the InceptionResNetV2, InceptionV3, DenseNet121, Xception, ResNet50V2, VGG19, and EfficientNetB7 networks.	Over 97 % of classifications were accurate in this experiment, which provided a network's performance overview. Subsequently, we focused on tumor detection using the Brain MRI Images for Brain Tumor Detection and The Cancer Genome Atlas Low-Grade Glioma database. The development encompasses learning transfer, data augmentation, as well as image acquisition sequences; T1-weighted images (T1WI), T1-weighted post-gadolinium (T1-Gd), and Fluid-Attenuated Inversion Recovery (FLAIR). Based on the results, using learning transfer and data augmentation increased accuracy by up to 6 %, with a p-value below the significance level of 0.05. As well, the FLAIR sequence was the most efficient for detection. As an alternative, our proposed model proved to be the most effective in terms of training time, using approximately half the time of the second fastest network.
Taher, F et al., 2022¹³	United Arab Emirates	In this paper, transfer-learning-based models in addition to a Convolutional Neural Network (CNN) called BRAIN-TUMOR-net trained from scratch are introduced to classify brain magnetic	A comparison between the pre-trained InceptionResNetv2, Inceptionv3, and ResNet50 models and the proposed BRAIN-TUMOR-net is introduced. The performance of the proposed model is tested on three publicly available Magnetic Resonance Imaging (MRI) datasets. The simulation results show that the BRAIN-TUMOR-net achieves the highest accuracy compared to other models. It achieves 100%, 97%, and 84.78% accuracy levels for three

		resonance images into tumor or normal cases.	different MRI datasets. In addition, the k -fold cross-validation technique is used to allow robust classification. Moreover, three different unsupervised clustering techniques are utilized for segmentation.
Khan, MSI et al., 2022¹⁴	Bangladesh	This paper proposes two deep learning models to identify both binary (normal and abnormal) and multiclass (meningioma, glioma, and pituitary) brain tumors. We use two publicly available datasets that include 3064 and 152 MRI images, respectively.	The confusion matrix and the ROC curve for the Figshare dataset. In the Figshare dataset, a “23-layers CNN” architecture was used for the prediction purpose. It can be observed that a total of 140, 270, and 180 MRI slices are correctly classified for meningioma, glioma, and pituitary tumors, respectively. While only 20 MRI slices are misclassified by the proposed architecture. The other performance metrics, including accuracy, precision, recall, FPR, TNR, and F1-score. The prediction accuracy of 96.7%, 97.2%, and 99.5% are achieved for meningioma, glioma, and pituitary tumors, respectively. Finally, the overall prediction accuracy achieved on the Figshare dataset is 97.8%. For the other performance metrics, we achieve an average precision of 96.5%, a recall of 96.4%, and an F1-score of 96.4%. The false-positive rate is approximately 0, and the true negative rate appears to be close to 1, which demonstrates that the “23-layers CNN” architecture can achieve excellent efficiency on the Figshare dataset.
Maqsood, S et al., 2022¹⁵	Lithuania	The proposed method has five steps. In the first step, a linear contrast stretching is used to determine the edges in the source	The proposed method was demonstrated on BraTS 2018 and Figshare datasets. Experimental study shows that the proposed brain tumor detection and classification method outperforms other methods both visually and quantitatively, obtaining an accuracy of 97.47%

		image. In the second step, a custom 17-layered deep neural network architecture is developed for the segmentation of brain tumors. In the third step, a modified MobileNetV2 architecture is used for feature extraction and is trained using transfer learning. In the fourth step, an entropy-based controlled method was used along with a multiclass support vector machine (M-SVM) for the best features selection. In the final step, M-SVM is used for brain tumor classification, which identifies the meningioma, glioma and pituitary images.	and 98.92%, respectively. Finally, we adopt the eXplainable Artificial Intelligence (XAI) method to explain the result.
Gao, P et al., 2022¹⁶	China	This study retrospectively analyzed MRI data of patients with brain tumors collected from 2000 to 2019 at the Beijing Tiantan Hospital in China. The presence of a pathologically confirmed, single	Among 37 871 patients (mean [SD] age, 41.6 [11.4] years; 18 519 women [48.9%]) included in the training data set, data from 11 716 patients were labeled with exact tumor masks and used for training the segmentation model. Four test data sets included a total of 1339 patients (Beijing Tiantan Hospital: 300 patients; Jilin University Affiliated Hospital: 71 patients; Shanxi Hospital: 99 patients; and

		brain tumor with the availability of pretreatment MRI scans were the inclusion criteria.	301 Hospital: 869 patients). The internal test data set collected for the evaluation of DLS assistance included 1166 patients.
Mahmud, MI et al., 2023¹⁷	USA	The methodology is divided into a few important stages. First, we collected our data from an available online source, then we pre-processed our datasets. We used the holdout validation system in the validation stage. We applied various machine learning models to train our images. Our dataset was split into three groups: 80% for training, 10% for testing, and 10% for validation.	The results of various types of developed deep learning models—i.e., the VGG16, CNN, ResNet-50, and Inception V3 classification algorithms—on the brain tumor MR image dataset are analyzed, and comparisons are shown. We present the performance of the models with respect to the accuracy, area under the curve (AUC), recall, and loss function results. After analyzing the methods of the CNN, VGG16, ResNet-50, and Inception V3, it was observed that the CNN outperformed the other deep learning models based on the findings. The CNN achieved a validation accuracy of 93.3%, a validation AUC of 98.43%, a validation recall of 91.1%, and a validation loss of 0.260.

DISCUSSION

Brain tumors (BTs) are a significant burden on people's health and on public healthcare, due to the poor prognosis of malignant subtypes (average five-year survival of 35%). Worldwide, 308,102 new cases of primary brain and CNS cancers were diagnosed, and 251,329 people died from these malignancies in 2020. In the era of precision medicine, an early diagnosis and an accurate follow-up are needed for better patient care. In this scenario, magnetic resonance imaging (MRI) significantly contributes to diagnosis and plays a key role in therapy planning and in evaluating treatment response and/or recurrence. The evolution of MR equipment and techniques has gone hand in hand with the ever-increasing needs of clinicians (surgeons, oncologists, radiotherapists), so that the current state of neuroimaging has evolved into a comprehensive diagnostic tool that allows for the characterization of morphologic as well as functional, hemodynamic, metabolic, cellular, microstructural,

and sometimes even genetic information of BTs.^{18,19}

MRI is the leading imaging modality in patients with primary intra-axial BTs. Computed tomography (CT) has limited indications, mainly in emergency settings (detection of intratumoral acute hemorrhage or critical mass effect as cerebral herniation or hydrocephalus) or, less frequently, in detection/confirmation of calcifications. A standard MRI protocol for BTs should always include T2 weighted (T2w) sequences in at least two orthogonal planes (i.e., axial and coronal), 2D or preferably (if available) 3D-FLAIR (fluid-attenuated inversion recovery), high-resolution 3D T2* gradient echo sequences as susceptibility weighted imaging (SWI), axial pre- and post-contrast T1 weighted sequences, the latter preferably with 3D high-resolution iso-volumetric sequences (such as spoiled gradient recalled acquisition or similar), which are useful in pre-treatment workup for intraoperative MR guided navigational system or for stereotactic radiotherapy (RT) planning.^{2,18,20}

The use of advanced MR imaging techniques, such as diffusion-weighted MR imaging (DWI) and perfusion MR imaging, is rapidly expanding in the field of neuro-oncology for diagnosing brain tumors, guiding surgical procedures, as well as monitoring the tumor treatment response. Water diffusion is substantially decreased in the setting of increased tumor cellularity, and perfusion MR imaging techniques assess tumor vascularity associated with neoangiogenesis. Recently, these have rapidly become the modalities of choice for detecting, characterizing or even staging viable tumor lesions, especially in malignant brain tumors, including glioblastomas, metastatic tumors, and lymphomas.^{21,22}

MR hardware, such as gradient coils used for advanced MR imaging, have been greatly improved recently and new MR techniques have emerged based on a variety of pathophysiologic backgrounds. In DWI, intravoxel incoherent motion (IVIM) is entering the clinical field for evaluating tissue perfusion without the use of contrast agents and

allowing separation of microcirculation from true water molecular diffusion. Diffusion kurtosis imaging (DKI) can analyze non-Gaussian diffusion through high diffusion weighting and is increasing the sensitivity to tissue features as well as providing information regarding the deviation from unrestricted diffusion associated with complex cytoarchitectonic environment. Perfusion MR imaging techniques have often been used in the evaluation of malignant brain tumors and consist primarily of three methods: dynamic susceptibility contrast (DSC) perfusion MR imaging; dynamic contrast-enhanced (DCE) perfusion MR imaging; and arterial spin labeling (ASL).^{21,23,24}

By using MRI imaging, radiologists easily analyze the pathology of a patient's mind that uses the strategy called CT (computed tomography). Image inspection is used not only for the underlying diagnosis but also for planning, assessing the treatment plan's feasibility, and other aspects of clinical consideration. X-ray image preparation depicts the cerebrum's

life structures in various planes and reveals data about static structures, as well as data about fundamental tissue uprightness and smooth motion. It is entirely possible that MRI-based screening for brain tumors may become feasible in the future.^{25,26}

CONCLUSION

In conclusion, MRI plays a major role in the diagnosis, grading, treatment and treatment response assessment of brain tumours and other intracranial lesions. Several adjunct MR imaging techniques have been developed to quantitatively measure a number of biophysical properties of brain tissue in vivo, allowing regional changes in the tissue microstructural environment to be better characterised. These techniques include diffusion-weighted imaging (DWI), perfusion-weighted imaging (PWI) and magnetic resonance spectroscopy (MRS). DWI provides information about cellularity and water movement, PWI provides information about angiogenesis and vascularity and MRS provides information about the composition of various metabolites within the tissue.

DISCLOSURE STATEMENT

Disclosure Statement : The authors have no conflicts of Interest to declare.

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