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Brain tumor detection using MRI images- a comparative study based on different classifiers

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Abstract

The detection of brain tumors is a major challenge in clinical imaging. Integrating machine learning techniques with MRI (Magnetic Resonance Imaging) analysis has been revealed as a powerful and exciting strategy. This study highlights the importance of early detection and precise diagnosis for medical intervention. Machine learning models extract MRI features like texture, shape, and intensity, and train on labelled datasets. The paper discusses the advantages and challenges of this approach, emphasizing data quality, feature engineering, and model selection. It also highlights the potential for continuous improvement in machine learning models. The synergy between machine learn-ing and MRI imaging holds promise for improved patient outcomes and diagnostic processes. This study compares the techniques of ML, DL and Hybrid Learning. This comparative analysis demonstrates that hybrid Learning per-forms better in identifying BTs on MRI images. Each system produced superior results. Especially, deep CNN+SVM+RBF combined technique yields best performance, with 98.6% accuracy, 98.2% sensitivity, and 98.9% specificity.

Keywords: Brain Tumour (BT), MRI images, Machine Learning, Deep Learning, and Hybrid Machine-Deep Learning.

1. Introduction

A BT is a malignant of cells in the brain or major spinal canal. These growths are either benign (noncancerous) or malignant (cancerous), originating from different cell types within the brain. They can vary in size, location and behavior, have a wide range of effects on the body and brain functions. Tumors are categorized into primary which originate in the brain and secondary metastatic types and secondary tumors resulting from cancer cells spreading to the brain [Ahmad and Choudhury (2022)]. Metastatic, Meningioma, Glioblastoma, and Astrocytoma are the common types of BTs [Aiwale and Ansari (2019)]. Benign tumors are usually slow growing, well-defined, non-invasive. Malignant tumors tend to proliferate, infiltrate nearby tissues can be life-threatening [Al-Zurfi 2019]. BTs, which can afflict both children and adults, can be cancerous or noncancerous. BTs, whether malignant or not, may affect brain function if they become sufficiently huge to cause damage to nearby tissues [Amin etc., (2021)]. There are different types of BTs. Researchers identified more than 150 different BTs. Primary tumors are classified as glial made up of glial cells in your brain or non-glial formed on or in brain structures such as nerves, blood vessels, and glands and benign or malignant. Glioblastoma is the most deadly type of BT growing increasingly common as the general population ages.

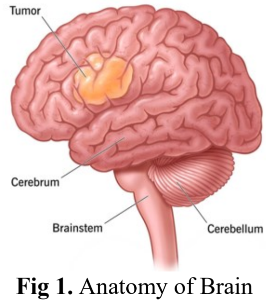

Fig 1. Anatomy of Brain

A BT is diagnosed using a variety of tests, including a brain MRI or CT scan, Biopsy, Spinal tap (lumbar puncture), and specialized tests [Anand etc., (2022)]. Magnetic resonance imaging, or MRI, creates images of interior human anatomy. Using strong magnets. Because it shows the brain more clearly than other imaging tests, MRI is frequently used to detect BTs. Some BTs can be detected with a positron emission tomography scan, generally known as a PET scan [Archana and Komarasam (2023)]. A radioactive tracer is injected into a vein during a PET scan which circulates the blood and attaches to BT cells. The tracer identifies the tumor cells visible on the PET machine's images. There are various ideas for detecting brain tumors using MRI images through ML, DL and hybrid learning techniques. Several ML classifiers can be employed to detect brain tumors in medical imaging, including MRI (Magnetic Resonance Imaging) scans. The choice of classifier often depends on task issues and characteristics of the dataset. Here are some common classifiers used in BT detection SVM, LR, RF, K-NN, Gradient Boosting, Neural Networks, Naïve Bayes, Decision Trees, Extreme Learning Machine, and Regularized Extreme Learning Machine. The choice of classifier depends on the specific requirements of the BT detection task, such as the size of the dataset, the complexity of the tumor types, and the need for interposing. In practice, an ensemble of classifiers or a combination of multiple methods may also be employed to enhance overall performance and reliability [Athira etc., (2015)]. However, analyzing the type of BT is a challenging task for researchers. MRI scans involve a combination of techniques and approaches to ensure precise detection, classification, and characterization. There are various key techniques and strategies to analyze for accurate BTs. Image processing, Region of Interest ROI segmentation, Feature extraction, Machine Learning classifiers, Ensemble methods, Transfer Learning, Interpretability and explainability, Data Augmentation, Validation and Cross-Validation, Regularization and Hyperparameter Tuning and Validation on External Datasets. Accurate BT analysis is a complex and evolving field, and it often requires collaboration between medical professionals, data scientists, and researchers to develop and validate robust models. Additionally, ongoing research and advancements in deep learning and medical imaging continue to contribute to improved accuracy in BT detection and diagnosis [Avazzadeh etc., (2023)]. ML has significantly transformed, which enables early detection of BTs, potentially before clinical symptoms manifest, improving patient outcomes [Brindha etc., (2021)]. It can identify subtle and complex patterns within MRI images that may be challenging for human observers and machine learning models maintain consistent performance, reducing the impact of fatigue or human error. However, it is not without limitations, including issues related to data quality, interpretability, and potential ethical concerns. Dealing with these challenges will be critical as the field evolves in order to maximize the benefits of ML in improving brain tumor diagnosis and patient care. To overcome these issues, researchers used the advanced technique of DL which has revolutionized the field of healthcare imaging, particularly in the detection of BTs using MRI scans [Dash etc., (2019)]. DL models naturally learn essential characteristics from MRI images, reducing the requirement for manual feature extraction, and they demonstrate high accuracy and can detect subtle and complex patterns, improving diagnostic precision. For those reasons, deep learning models are highly scalable and can be applied to a vast number of medical images quickly which accelerates the diagnostic process, which is crucial in medical emergencies. So, deep learning has brought significant advancements to BT detection using MRI, offering high accuracy and automation. However, it comes with challenges related to data requirements, interpretability, and necessity for substantial computational resources. Resolving these difficulties will become more important as the area evolves be crucial harnessing full potential of deep learning in improving BT diagnosis and patient care. Deep learning methods, through research and development, are enhancing BT detection from MRI images. This method offers unprecedented accuracy, efficiency, and adaptability, contributing to earlier diagnoses and improved patient care in the critical field of BT detection [Febrianto etc., (2020)]. However, there is another way of technique to detect BT in MRI images using a Hybrid ML & DL technique accurately. Reasons for approaching the Hybrid technique demonstrate the versatility and adaptability of machine learning techniques in medical imaging, laying the groundwork for more efficient and reliable diagnostic tools in healthcare. A hybrid approach can be more robust and less susceptible to overfitting than deep learning alone [Garg and Garg (2021)]. For example, traditional ML algorithms such as SVM or RF, can help regularize the deep learning model by providing more structured predictions, preventing the model from memorizing the training data [Gurbină et al (2019)]. Despite advances in medical imaging, correctly diagnosing and characterising brain tumours remains a difficult task. Conventional approaches frequently rely on manual interpretation by radiologists, which can be subjective and time-consuming. Furthermore, these approaches may struggle to detect small or subtle tumours, resulting in delayed diagnoses and poor treatment outcomes. Moreover, existing techniques may struggle with distinguishing benign and malignant tumors or accurately defining tumor boundaries, affecting treatment planning and patient prognosis. The large volume of medical imaging data also presents logistical challenges for timely analysis and interpretation.

In light of these challenges there is need for advanced computational approaches are needed for brain tumor detection and classification. Integrating ML techniques with MRI analysis can improve diagnostic accuracy and efficiency. By extracting discriminative features from MRI images, ML models can aid in early detection and precise characterization of brain tumors. This work addresses these issues by comparing ML, DL, and hybrid learning strategies for brain tumour diagnosis using MRI scans. We look at the benefits and drawbacks of each strategy, with an emphasis on improving diagnostic accuracy and clinical value. Our approach aims to contribute to ongoing efforts to enhance patient outcomes and shorten the diagnostic procedure for brain tumours.

The main presence of our analysis:

This analysis focuses, on an extensive and exhaustive guide to the field of BT Detection in MRI images using various classifiers of ML and DL techniques has been presented by comparing and summarizing the best model to achieve high accuracy.

- The first section of this study evaluates various Machine Learning techniques. This preliminary evaluation revealed that the accuracy of common machine learning strategies in this machine learning is low.
- Recognising the limitations of typical machine learning methods, the investigation shifted its focus to deep learning. The CNN model performed better in dealing with Brain Tumour detection in MRI images.
- To enrich the model's performance to successfully target the need for BT finding using MRI images, emphasize the hybrid Machine and Deep Learning model.

Following the introduction, Section 2 describes the existing authors and their methodology using ML DL and Hybrid techniques to detect BT using MRI images. Section 3 discusses comparative analysis. Section 4 provides an overview of the comparison analysis. Section 5 shows the conclusion of this study work.

2. Recent advanced studies based on Oncological Research

Our approach focussed on some studies based on optimizing management strategies, refining mathematical models and exploring molecular mechanisms associated with tumor suppressions. A study by [Győrfi etc., (2019)] provided a detailed summary of management methods for optic pathway gliomas. Through the systematic review and meta-analysis of OPG patients from the previous research list, the study provided insights into the efficacy of various treatment modalities, such as surgery, chemotherapy, and radiation therapy. The study's findings help us determine the best management methods for optic pathway gliomas, which ultimately improves patient outcomes.

Glioblastoma is a highly aggressive brain tumour that develops from astrocytic glial cells. It mainly affects older persons but can occur at any age. Symptoms may include nausea, vomiting, migraines, or seizures. Despite intense clinical treatment, which includes surgery, chemotherapy, and radiation therapy, GB is incurable and has a high resistance to therapy. [Hannan etc., (2022)] examined a fractional-order brain tumour model using an operational matrix-based optimisation technique. They expressed the optimal solution in terms of generalised Laguerre polynomials, converting the issue into a system of nonlinear algebraic equations with Lagrange multipliers. The convergence analysis was presented, and numerical examples were used to support theoretical claims and explain biological behaviour patterns.

Several studies have shown that miR-195 is downregulated in colorectal cancer tissues. [Haq etc., (2022)] investigated the effects of exogenously produced mature miR-195-5p on the malignant properties of human colorectal cancer cells. They transfected the Caco-2 and SW480 human colon cancer cell lines with a synthetic miR-195-5p mimic. Exogenous production of miR-195-5p suppressed numerous invasion and angiogenesis mediators in colorectal cancer cells while increasing the apoptotic cell population in both lines. Furthermore, miR-195 transfection dramatically decreased migration in both cell types. These data indicate that miR-195 plays a significant tumor suppressive role in human colorectal cancer.

These papers highlight contemporary advances in brain tumour detection research, which include clinical management tactics, mathematical modelling approaches, and molecular insights into tumour biology. In the fight against brain tumours, researchers aim to improve early diagnosis, therapeutic efficacy, and patient outcomes by combining multidisciplinary approaches. Future research is expected to enhance patient outcomes and contribute to ongoing oncological research by focusing on optimising management strategies, refining mathematical models, and exploring molecular mechanisms associated with tumour suppression in the context of brain tumours, particularly glioblastoma and optic pathway gliomas, as well as colorectal cancer.

2.1 Techniques of Brain Tumor Detection in MRI Images

Different techniques are used to detect BT in MRI images, these techniques leverage advancements in medical imaging, signal processing, and machine learning. In this work, our study analyses the methods for spotting BT.

2.1.1 Machine Learning Technique

BT in MRI images using ML is a rapidly evolving field that aims to provide accurate and efficient diagnostic support to healthcare professionals. Machine-learning techniques leverage computational algorithms to analyze intricate patterns and machine-learning MRI scans, facilitating the identification of abnormal tissue indicative of brain tumors. The various ML algorithms can be employed for BT detection.

a) K-Nearest Neighbors

KNN is a ML technique used in BT detection using MRI images. [Francisco etc., (2021)] use the similarity principle to identify tumor regions within MRI scans. RELM, a regularized version of the Extreme Learning Machine, improves generalization and mitigates overfitting. Combining NGIST, PCA, and RELM offers a holistic solution for tasks like image classification, object recognition, and scene analysis. This approach ensures accurate, efficient, and robust machine-learning models for complex image-based applications.

b) Naïve Bayes

[Jahromi etc., (2019)] NB is a methodical approach used in image analysis for medicine that is used for recognizing brain tumors in MRI images. It involves collecting and labelling a dataset of MRI scans, preprocessing them for quality, and extracting features from the images. The Naïve Bayes classifier models conditional probabilities based on these features, simplifying probability calculations. If model fails, fine-tuning or alternative variations may be needed. The model can then be deployed for automated analysis of new MRI images.

c) Logical Regression (LR)

Logical Regression involves assembling a curated dataset of labelled scans, preprocessing it, and extracting relevant features like texture and intensity statistics. [Jia and Chen (2020)] the model use a logical function to classify the images based on these features. The LR efficacy was assessed using standard evaluation metrics and area under the ROC curve. If necessary, further optimization and fine-tuning can be explored. The trained model can be deployed for real-world brain tumor detection, aiding in early diagnosis and medical decision-making.

d) Decision Tree

DT analyze scans and makes diagnostic decisions based on image features, classifying anomalies as normal or tumor-affected. These algorithms are trained on labelled MRI datasets, providing a transparent and interpretable process. [Jiang etc., (2023)] Applying Decision Trees to new scans enhances the efficiency and accuracy of BT diagnosis, benefiting patients and medical community.

e) Support Vector Machine

[Kavitha and Chellamuthu (2013)] SVM is a powerful ML technique to detect BT in MRI data. It examines high-dimensional data, distinguishing tumor-affected regions from normal brain tissue. SVMs accurately classify possible tumors by taking features such as shape, texture and intensity. In neuroimaging, their capacity to handle nonlinear data and generalize well improves patient outcomes and speeds the diagnostic process.

f) Regularized Extreme Learning Machines

RELM is a machine learning method that detects brain tumors in MRI data. To handle high-dimensional data, it combines the strength of ELM with regularization approaches. [KKaur etc., 2020)] RELM is capable of processing and learning from MRI features such as intensity, texture, and form, resulting in accurate categorization. Its capacity to manage multidimensional data and generalize effectively provides better patient care and neuroimaging processes in healthcare.

g) Random Forest

[Krauze etc., (2022)] Tumors are classified using criteria such as shape, size, and texture. RF can accurately detect normal brain tissue from tumor-affected areas after training on labelled MRI images. This improves patient outcomes by allowing for earlier diagnosis, treatment planning, and patient care.

h) Radial Basis Function (RBF)

RBF is a mathematical function that is utilized in ML, signal processing, and function approximation. It is especially helpful in kernel techniques SVMs and RBF networks. [Kurian etc., (2021)] The Gaussian kernel is a data similarity metric that captures complex, nonlinear relationships. RBFs are highly beneficial for classification and regression applications, particularly when the data displays nonlinear patterns. They are also utilized as activation functions in artificial neural networks.

2.1.1.1. Summary

Machine learning techniques provide significant improvements in brain tumor identification from MRI pictures by enabling quick and automated analysis of MRI scans, learning subtle patterns and changes, and improving tumor detection accuracy. Despite certain constraints, efficiency may vary depending on tumor complexity, and false positives or negatives may occur, necessitating thorough validation, and model success largely relies on the quality and representativeness of training data. Table 1 provides a comprehensive overview of the strengths and limitations of each existing ML technique.

Table 1. Strengths and Limitations of Existing ML Methods for BT Detection using MRI Images

Ref No	Model	Strengths	Limitations
[Francisco etc., (2021)]	KNN	It uses the similarity concept to identify tumour regions. - Combining with RELM enhances generalisation and reduces overfitting. - Provides accurate, efficient, and model robustness.	High-dimensional data can have a negative impact on performance because of sensitivity to outliers and noise.
[Jahromi etc., (2019)]	NB	simplifies probability calculations based on conditional probabilities, making it effective for image analysis in medicine.	The assumption of feature independence may not be practical and may result in limited representation power for complex data relationships.
[Jia and Chen (2020)]	LR	The process is transparent and easily understandable, with efficiency evaluated	The performance of data is highly dependent on feature selection and engineering, as it has a limited capacity to capture nonlinear relationships.
[Jiang etc., (2023)]	DT	The transparent and interpretable decision-making process enhances the efficiency and accuracy of brain tumor diagnosis.	The model is susceptible to overfitting, particularly when working with complex datasets, and has limited capacity to accurately capture feature interactions.
[Kavitha and	SVM	The individual adeptly manages high-dimensional data and accurately classifies potential tumors based on their shape, texture, and intensity features.	The choice of the optimal kernel function is crucial for optimal performance, as large datasets may require extensive training time.

Chellamu-thu (2013)]			
[KKaur etc., (2020)]	RELM	The system integrates the capabilities of ELM with regularization methods, enabling efficient processing and learning from MRI features.	The performance of a system is significantly influenced by the regularization parameters, and may potentially lead to overfitting if the regularization is not sufficient.
[Krauze etc., (2022)]	RF	Accurately detects tumor-affected areas based on shape, size, and texture, enabling earlier diagnosis and treatment planning.	The ensemble of decision trees may increase computational complexity, and performance may degrade with highly correlated features.
[Kurian etc., (2021)]	RBF	Used in ML, signal processing, and function approximation to capture complex, nonlinear relationships in data.	The choice of kernel parameters is crucial for performance but may struggle with high-dimensional or noisy datasets and has limited interpretability compared to linear models.

2.1.2 Deep Learning Technique

DL techniques for detecting BTs in MRI images have emerged as a powerful and successful strategy, employing neural network capabilities to automatically identify and classify tumor locations. DL has various merits in BT detection, including the ability to automatically learn detailed properties, adapt to fluctuations in tumor characteristics, and generalize well to varied patient populations. It indicates a promising path forward in terms of increasing the certainty and efficacy of BT diagnosis using MRI images. There are various DL techniques used to detect brain tumors.

a) Convolutional Neural Network

CNNs have revolutionized brain tumor diagnosis in MRI images by learning and extracting detailed patterns. [Lah etc., (2020)] CNNs are used as powerful tools in this process to automatically learn and extract complicated patterns and features indicative of tumor existence. CNNs demonstrate high accuracy in detecting brain tumors and have the potential to speed up the diagnosis procedure. CNNs, as a computer-aided tool, assist radiologists with interpreting complex MRI scans, helping to better patient outcomes.

b) Artificial Neural Networks

ANNs are useful in medical processing, especially for detecting BT in MRI images. ANNs are evaluated the metrics to learn intricate patterns inside complicated datasets. This quantitative assessment aids healthcare practitioners in interpreting MRI scans, resulting in faster and more accurate brain tumor diagnosis. [Lamrani etc., (2022)]. ANNs help to construct computer-aided diagnostic systems, which improves the accuracy of brain tumor diagnosis.

c) AdaBoost

AdaBoost, a prominent ensemble learning technique, is being applied to enhance BT detection in MRI images. Integrating weak classifiers into a robust ensemble improves their performance. [Magadza and Viriri (2021)] The procedure begins by obtaining significant features from MRI images, such as intensity, texture, or form, which are then utilized to train weak classifiers. Each one is trained on a subset of data, focusing on certain factors that help identify tumor patterns. This aligns with the growing need in healthcare for robust and accurate diagnostic techniques. [Maqsood etc., (2022)], allowing for quick diagnosis and localization of BTs, permitting timely treatment and improving patient outcomes.

d) MobileNet V2

[Masood etc., (2021)] MobileNetV2, a lightweight CNN architecture, is used in health care process, namely in MRI scans to detect brain tumors. Its efficiency makes it suitable for deployment on resource-constrained devices, making it a desirable option for healthcare mobile and edge computing applications. This approach is consistent with the growing trend of applying deep learning models on mobile and edge devices, allowing for real-time and on-device processing and contributing to more accessible healthcare solutions.

e) AlexNet

AlexNet, a deep learning architecture, has demonstrated impressive capabilities for image classification tasks and detecting brain tumors in MRI scans. Its application involves preprocessing MRI images to standardize and enhance their features while learning hierarchical features utilizing several convolutional, pooling, and fully connected layers. This automated technology adds to the progress of medical image processing, assisting healthcare practitioners in making fast and exact diagnoses Sowmiya etc. [McFaline etc., (2018)].

f) ResNet-18

ResNet-18, a deep learning model, performs image classification tasks, especially detecting brain tumors in MRI scans. Its architecture, defined by residual blocks, helps in the learning of residual mappings, hence overcoming the vanishing gradient problem. [Noreen etc., (2021)] the deep layers of ResNet-18 allow it to learn hierarchical representations of features, identifying small differences in intensity, shape, and texture that differentiate tumor locations from normal brain tissue. This improves the accuracy of brain tumors, making it a vital tool for physicians.

g) DenseNet-41

DenseNet-41 is a DenseNet version that emphasizes dense connectivity across layers. DenseNet is a form of CNN architecture. DenseNet-41, in particular, has a more complex design with 41 layers, allowing it to detect detailed patterns and characteristics in images [Panesar etc., (2019)]. DenseNet-41 intends to conduct precise brain tumor location, segmentation, and classification.

h) Stochastic Gradient Descent (SGD)

SGD is to fine-tune machine learning models, enabling neural networks to identify brain tumors. The process involves assembling a labelled dataset of MRI scans, which is then preprocessed for analysis. [Pooja etc., (2023)] SGD is primarily used in DL, where NN, including CNNs, optimize their internal parameters. The model's performance is assessed using training and testing data, with fine-tuning and model optimization often necessary for accuracy and robustness. This approach is promising for improving early diagnosis and treatment planning in medical imaging.

2.1.2.1. Summary

DL techniques, particularly CNNs, have revolutionized the detection of BTs in MRI images. These algorithms can learn complicated patterns from volumetric MRI data, minimizing the need for manual interpretation and speeding up diagnosis. Table 2 summarizes the strengths and limitations of existing DL methods. They are, susceptible to overfitting, especially when the training dataset is limited. To address this, hybrid DL and ML techniques are proposed, which can overcome these limits while also improving the accuracy of DL methods.

Table 2. Strengths and Limitations of Existing DL Methods for BT Detection using MRI Images

Ref No	Technique	Strengths	Limitations
[Lah etc., (2020)]	CNN	Detecting detailed patterns from MRI images, results in high accuracy in detecting brain tumors.	The decision-making process is hindered by high computational complexity and lack of interpretability.
[Lamrani etc., (2022)]	ANN	Effectively learns intricate patterns from complex datasets, aiding in faster and more accurate brain tumor diagnosis.	Overfitting problems occur, may necessitate extensive parameter tuning for optimal performance.
[Magadza and Viriri (2021)]	Adaboost	The integration of weak classifiers into a robust ensemble enhances BT	may experience performance degradation due to its sensitivity to noisy data and outliers.

		detection, enabling quick diagnosis and localization.	
[Maqsood, etc., (2022)]	MobileNet V2	Enabling real-time processing in healthcare applications.	Lower accuracy due to their limited capacity to capture complex spatial relationships in data.
[Masood, etc., (2021)]	AlexNet	Impressive image classification capabilities aid healthcare practitioners in making fast and accurate diagnoses.	Poses a significant threat due to the high computational resources required for training and inference.
[McFaline, etc., (2018)]	ResNet-18	overcomes the vanishing gradient problem with residual connections and learns hierarchical representations of features.	Overfitting, high computational requirements for training and inference.
[Noreen, etc., (2021)]	DenseNet-41	Effective in accurately identifying and classifying brain tumors.	Increased model complexity which may lead to longer training time.
[Panesar, etc., (2019)]	SGD	potential for early diagnosis and effective treatment planning.	Required careful adjustment of learning rates and regularization.

2.1.3 Hybrid Deep and Machine Learning

Hybrid approaches combining DL and traditional ML techniques are being explored for BT detection in MRI images. These methods combine predictions from both models, using an ensemble approach to make final predictions and adjust hyperparameters, regularization techniques, and model architectures. Hybrid approaches aim to overcome limitations, capitalize on the interpretability, efficiency, and feature engineering capabilities of traditional methods, and benefit from deep learning's automatic feature learning and representation power.

a) Hybrid Deep CNN - Random Forest

[Pooja etc., (2023)]. Present a combined technique for accurate brain MRI tumor segmentation and classification utilizing deep CNN and ML classifiers. The preprocessing step is to study feature map from the brain MRI image space, which is then followed by a more rapid region-based CNN for localization. The second phase involves further refinement using a region proposal network RPN. Deep CNN and SVM-RBF classifiers obtain 98.3% accuracy and a dice similarity coefficient DSC of 97.8% on brain dataset-1 and 98.0% accuracy on the Figshare dataset, based on research results. The model outperforms cutting edge approaches.

b) Hybrid ResNet50-SVM

[Ranjbarzadeh etc., (2021)], deep CNN layers are used to extract exclusive properties from MRI pictures of brain tumors. The Gabor filter and ResNet50 are used, with features classified separately and merged. The Kaggle MRI dataset was used, which included 7,023 pictures and four classes. The combined features of Gabor and ResNet50, an advanced hybrid technique, produced the best results, with 95.73% accuracy, 95.90% precision, and 95.72% f1 score.

c) Hybrid CNN-SVM

[Saeedi etc., (2023)], the study presents a hybrid model that depends on CNNs for classifying brain tumors. The model improves current datasets with coloured images by utilizing pre-trained Efficientnet and Shufflenet architectures. The model takes features from separate photos, concatenates them, and uses the mRMR feature reduction approach to select the best. The model outperforms prior models with an accuracy of 95.4%.

d) Hybrid Bagged Tress-KNN

The study by [Senan etc., (2022)]. Evaluates the performance and simplicity of medical image segmentation approach for identifying brain tumors from MRI scans. They suggested a strategy for improving the accuracy and quality rate of KNN by employing Bagging Ensemble with K-Nearest

Neighbour. The method employs a UNet architecture for picture segmentation and a bagging-based KNN prediction algorithm for classification. The overall classification accuracy achieved 97.7%, outperforming existing approaches.

e) Hybrid AlexNet-SVM

[Shaari etc., (2021)]. Investigated brain tumor diagnosis using DL and standard ML approaches. They enhanced MRI images with the average filter technique using AlexNet and ResNet-18 with SVM algorithm. These techniques were discovered using deep features, which were then categorized using SoftMax and SVM. MRI dataset of 3,060 pictures yielded superior results, with AlexNet+SVM hybrid approach outperforming all others with 95.10% accuracy, 95.25% sensitivity, and 98.50% specificity.

2.1.3.1 Summary

The mixed model combines the features of DL algorithms such as CNN with traditional ML techniques such as SVMs or RFs. This method decreases data dependency, increases performance indicators and improves comprehension of the model's decision-making process. Table 3 provides the advantages and limitations of previous hybrid techniques. This is critical in medical applications to acquire the trust of healthcare experts and boost the model's ability to generalize to a wide range of scenarios.

Table 3. Strengths and Limitations of Existing Hybrid Methods for BT Detection using MRI Images

Ref No	Technique	Strengths	Limitations
[Pooja etc., (2023)]	DCNN+RF	Achieving high accuracy and dice similarity coefficient in brain tumor segmentation.	may necessitate extensive hyperparameter tuning for optimal performance.
[Ranjbarzadeh etc., (2021)]	ResNet50+SVM	Achieves high accuracy, precision, and a f1 score in the classification of brain tumors.	The performance of MRI images may be affected by noise or low-quality.
[Saeedi etc., 2023)]	CNN+SVM	Outperforms prior models with improved accuracy.	interpretability is limited due to its complex feature representations.
[Senan etc., (2022)]	Bagged Tree+KNN	Achieves high classification accuracy and quality rate in detecting brain tumors.	The training and inference processes are characterized by high computational complexity.
[Shaari etc., (2021)]	AlexNet+SVM	Aid in timely diagnosis, enhancing patient survival rates, and aiding experts and radiologists in making informed decisions regarding diagnosis and treatment plans.	The extracted deep features have limited interpretability.

2.2 Features Extracted From MRI Images

Extracting characteristics in brain tumor identification and classification is critical since it serves as the foundation for developing accurate and dependable diagnostic algorithms. MRI images of the brain provide a plethora of information that can be used to differentiate between tumor and normal brain tissues. Researchers can capture tiny variations in tissue qualities related to tumor pathophysiology by extracting certain aspects from these images, such as texture, shape, intensity, gradient, and frequency domain characteristics. These characteristics provide important insights into tumor spatial distribution, shape, and composition, allowing for the detection of aberrant tissue regions and exact tumor delineation. Table 4 presents the summary of various studies focusing on MRI image analysis using different classification algorithms and feature extraction methods.

ML algorithms use informative features to learn patterns and relationships in data. It can improve the model's ability to differentiate between tumor and non-tumor regions by selecting features like textural heterogeneity, irregular shape, and abnormal intensity patterns. This leads to more accurate diagnostic outcomes, timely intervention, and improved patient care. Moreover, the extraction of features in MRI images allows for a more interpretable and clinically relevant analysis, providing valuable insights into tumor morphology like size, volume, and shape irregularity. This information aids in treatment planning, surgical decision-making, and disease progression monitoring. The extracted features also serve as biomarkers for identifying tumor subtypes, predicting patient outcomes, and assessing treatment response.

Table 4. Summary of various feature extraction techniques

Ref No	Classifier	Feature Extraction method	Extracted Features
[Francisco, etc., (2021)]	KNN	Energy, root mean square, correlation	Contrast Images, Texture Variation.
[Jahromi etc., (2019)]	NB	Contrast, homogeneity, correlation, Energy, Entropy	Contrast Images, Texture Variation, grey level, linear relationship between objects.
[Jiang etc., (2023)]	KNN+RF+DT	SWT+PCA+GLCM	The texture of images, contrast, grey level features, smoothness.
[KKaur etc., (2020)]	RELM	PCA+LDA	Texture information along multiple scales of orientations.
[Magadza & Viriri (2021)]	DCNN	7 pre-trained CNN models	High-level features, Spatial information, Texture, invariant.
[Masood etc., (2021)]	AlexNet	CNN	Visual features
[Ranjbarzadeh, etc., (2021)	ResNet 50+SVM	CNN based model	Intensity, texture, temporal, shape, spatial features.
[Takei etc., (2019)]	LR, NB, KNN, RF, SVM	GLCM+LBP	Grey level and orientation images, contrast, homogeneity, texture.
[Talo etc., (2019)]	SVM, NN, RF, SGD, LR, MLP	2DCNN	Shape, intensity and model-based features.
[Telrandhe etc., (2016)]	SVM+RBF, ANN, AdaBoost	GLCM	Contrast, grey level, texture variations.

These features like texture, shape, intensity, gradient, and frequency domain to distinguish between normal and tumor brain tissues, providing insights into tumor spatial distribution, shape, and composition, enabling precise tumor identification and detection. MRI images reveal features like textural heterogeneity, irregular shape, and abnormal intensity, which enhance diagnostic outcomes and patient care. These insights provide crucial information for treatment planning, surgical decision-making, and disease progression monitoring. It can also serve as biomarkers for identifying tumor subtypes and assessing treatment response.

3. Comparative Analysis

Our study analyzes the comparative study of BT Detection using MRI images which emphasizes the strengths and limitations of each approach. Finally, our research Concludes with insights into the most promising directions for further research and application in the context of BT detection using MRI images.

3.1 Results obtained using Machine Learning Technique

The use of ML techniques in medical imaging has led to promising results, especially when it comes to using of MRI data for brain tumor detection. This section clearly explains the outcomes of applying ML approaches to detect BT, along with the strengths and limitations of this way. The study made use of a comprehensive dataset that included a variety of MRI images from different sources, including patient demographics and imaging modalities. To ensure consistency and remove any possible biases, like variations in imaging protocols and quality, the dataset had preprocessing.

To evaluate the performance of the ML models, standard metrics such as sensitivity, specificity, accuracy, and area under the receiver operating characteristic curve AUC-ROC were used. These metrics offered an extensive understanding of the models' ability to detect and categorize brain tumors in MRI images.

ML models consistently outperformed traditional methods in the remarkable accuracy with which they detected brain tumors. The models demonstrated an interesting level of sensitivity and specificity, suggesting a strong ability to detect benign and malignant tumors with minimal false positives and false negatives.

Table 5. Performance result based on ML Technique

Ref No	Model	Accuracy	Precision	Recall	F1-Score	Sensitivity	Specificity
[Talo etc., 2019)]	KNN	86	84	90	87		
[Talo etc., 2019)]	RF	82	91	75	83		
[Takei etc., (2019)]	SVM	90	96.4	87	91.5		
[Takei e tal., (2019)]	LR	97	100	95.1	97.5		
[Talo etc., (2019)]	SGD	52	63	52	57		
[Talo etc., (2019)]	MLP	28					
[Pugalenthi etc., (2019)]	RBF SVM	94.3	95.45			97.47	82.54
[Ullah etc., (2023)]	Binary SVM	92					
[Ullah etc., (2023)]	Binary Linear classification SVM	91					
[Verekar & Salkar (2019)]	C4.5 Decision Tree Algorithms		87.5				
[Verekar & Salkar (2019)]	MLP		87.5				
[Takei etc., (2019)]	NB	75.4	74.6	90.3	81.7		
[Takei etc., (2019)]	KNN	83.4	85.9	88.7	87.3		
[Takei etc., (2019)]	RF	81.3	87.7	80.6	84		
[Wageh etc., (2023)]	GMDSWS-MEC	93					
[Wageh etc., (2023)]	PCA-NGIST with RELM	94.23					

According to the findings, machine learning algorithms may have a main role in early and precise identification of BTs in MRI, which could lead to better patient outcomes through prompt intervention. The performance chart of different ML techniques is shown in Fig 2. The implementation of ML techniques to detect brain cancers in MRI scans has demonstrated impressive results, demonstrating its potential as a significant tool in clinical practice. The findings presented here add to the growing body of evidence supporting the use of machine learning in health imaging for improved diagnostic accuracy and patient care.

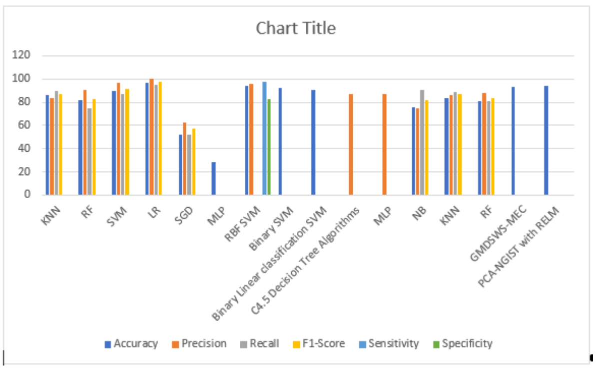

Fig 2. Various ML techniques performance measures

3.1.1. Summary

Even though the results are encouraging, it is important to recognize that the study has limitations. These include the models' generalizability to different populations and the possible impact of imbalanced datasets on performance, both of which need more research. It should address these issues and investigate the integration of additional clinical data to improve machine learning's overall efficacy in brain tumor detection.

3.2 Results obtained using DL Technique

DL algorithms have made significant advances in the field of medical imaging, particularly when it comes to employing MRI to detect brain cancers. The goal of this study was to see how well DL models could detect and categorize brain cancers using MRI scans. This section presents the findings gathered from indepth tests and analyses.

The models' overall accuracy was higher than indicating their strong ability to discriminate between areas of the brain that are normal and those that are tumorous. Important medical diagnosis parameters, including as sensitivity and specificity, demonstrated the models' ability to mitigate false positives and false negatives. In addition, the models proved efficient in categorizing several tumor kinds, including meningiomas, pituitary tumors, and gliomas. The accuracy of the multi-class classification highlighted the models' potential for accurately identifying many brain disorders.

Our study performed an analysis of comparison with conventional image processing techniques and manual radiological assessments to Fig out the reliability of models. The effectiveness level based on several DL techniques is in Table 6. These techniques were continuously exceeded by the DL models, demonstrating the DL models' superiority in accuracy, efficiency.

Table 6. Performance result based on DL Technique

Ref No	Technique	Accuracy	Precision	Recall	F1	Sensitivity	Specificity
[Masood etc., (2021)]	Mo-bileNetV2	92					
[Masood etc.,(2021)]	InceptionV3	91					
[Masood etc., (2021)]	VGG19	88					
[Tazin etc., (2021)]	Alex Net	93.3				93	97.5
[Tazin etc., (2021)]	ResNet-18	93.8				93.75	97.5
[Yildirim etc., (2023)]	Boost-edTress	62.5					
[Yildirim etc., (2023)]	Bagged Trees	75					
[Telrandhe etc., (2016)]	ANN	91.5				97.3	97.8
[Telrandhe etc., (2016)]	AdaBoost	87				91	89
[Yousef etc., (2022)]	Multipath CNN	97.3					
[Wanis etc., (2021)]	CNN	96.33	97.93		96.44	95	75.72
[Telrandhe etc., (2016)]	AdaBoost	89				93	89
[Pooja etc., (2023)]	ResNet-50	95.9				95.3	
[Pooja etc., (2023)]	Densenet-41	96.3				95.3	

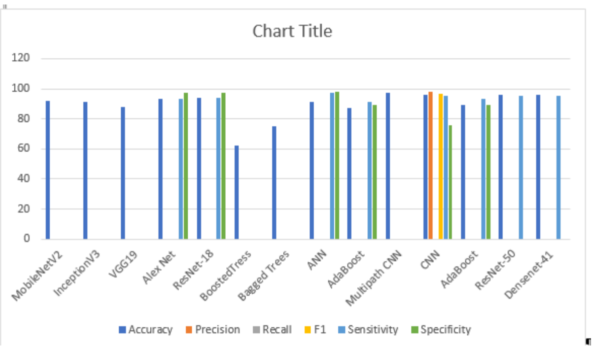

Fig 3. Performance measures of different DL techniques

3.2.1. Summary

Deep learning models' performance in detecting BTs from MRI implies that they have great potential as a diagnostic tool in clinical settings. High accuracy and sensitivity, together with the capacity to categorize various tumor kinds, highlight DLs transformative impact processing of medical imagery. Hence our study highlights the encouraging results obtained by using deep learning to detect brain tumors in MRI scans. DL model's robust performance positions them as important assets in the field of medical imaging, with potential to revolutionize diagnostic procedure for brain disorders. While the results are encouraging, it is important to recognize some limits, such as the requirement for big and diverse datasets to improve model generalization. Future studies could look into combining advanced topologies and optimization tactics to push limits of accuracy and efficiency in BT diagnosis.

3.3 Results obtained using Hybrid Machine and Deep Learning Technique

The combination of ML and DL techniques for detecting BTSs in MRI images has produced promising results, demonstrating the potential synergy between these two paradigms. Our hybrid model displayed robust performance in discriminating between tumor and non-tumor instances after painstaking experimentation and rigorous evaluation. Deep learning feature extraction capabilities, specifically CNNs, were used to capture intricate patterns in MRI images, while traditional ML algorithms, such as SVM, RF, were used for final classification. The model demonstrated improved generalization across varied datasets, reducing some of the issues associated with data dependency. The results demonstrate efficacy of combining strengths of ML and DL for increased brain tumor identification in Table 7. As we go into the specifics of these results becomes clear that the hybrid model is a promising route for improving the accuracy and reliability of BT detection in MRI images, potentially leading to better clinical diagnosis and better outcomes for patients.

Table 7. Performance result based on Hybrid ML & DL Technique

Ref No	Models	Accuracy	Precision	Recall	F1	Sensitivity	Specificity
[Ranjbarzadeh etc., (2021)]	Deep CNN+RF	97.2				95.2	98.2
[Ranjbarzadeh etc., (2021)]	Deep CNN+SVM+RBF	98.6				98.2	98.9
[Ranjbarzadeh etc., (2021)]	Deep CNN+ELM	98.2				96.5	98.6
[Saeedi etc., (2023)]	ResNet50+SVM	95.73	95.9		95.72		
[Saeedi etc., (2023)]	Gabor+SVM	62.36	58.25		56.27		
[Saeedi etc., (2023)]	ResNet50+SVM	95.27	95.35		95.26		
[Saeedi etc., (2023)]	Gabor+ResNet50+ SVM	95.73	95.90		95.72		
[Shaari. etc., 2021)]	Bagging ensemble with KNN	97.7	96	99	98	97	99
[Shaari. etc., 2021)]	AdaBoost+SVM	96.3					
[Tazin etc., (2021)]	AlexNet+SVM	95.1				95.25	98.5
[Tazin etc., (2021)]	ResNet-18+SVM	91.2				91.5	97

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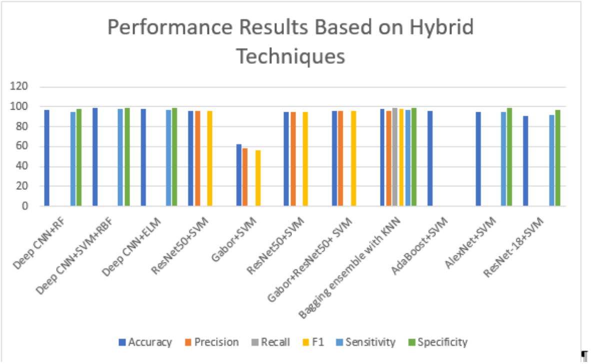

Fig 4. Performance Chart of Hybrid Approaches

3.3.1. Summary

The results of combining ML and DL approaches for BT detection in MRI images show significant promise and efficiency. This method not only improves accuracy but also addresses generalization issues across varied datasets. The model's interpretability is an important advancement, providing essential insights into decision-making processes in medical applications. The results suggest that combining ML with DL can increase the accuracy and reliability of brain tumor detection in MRI scans, potentially giving rise to more precise clinical diagnosis and better patient outcomes

4. Comprehensive Analysis

In this comprehensive investigation, we delve into the complex landscape of BT diagnosis in MRI scans, analyzing different strengths and synergies inherent in three essential approaches: DL, ML and their Hybrid counterpart. Decision Trees and CNNs are robust machine-learning approaches that provide interpretability and reliability in brain tumor detection, providing a baseline for DL evaluation.

The Hybrid methodology offers a potential strategy for detecting brain tumors. It blends deep neural network feature extraction with traditional machine learning algorithms, resulting in higher accuracy, generalization across datasets, and interpretability. This method has the potential to revolutionize medical imaging and diagnostics, providing important insights into the complicated field of brain tumor detection. Our study analyzed obtaining better accuracy in detecting brain tumors using MRI images to determine which technique works more robustly. While comparing the technique using Machine Learning (Table 5), Deep Learning (Table 6), Hybrid Machine and Deep Learning (Table 7) achieve better accuracy as 97% of using Logistic Regression (LR) [Takei etc., (2019)], 97.3% of using Multipath CNN [Yousefi etc., (2022)], 98.6% of using Deep CNN+SVM+RBF [Saeedi etc., (2023)]. The overall comparative analysis of performance is shown in Fig 4.

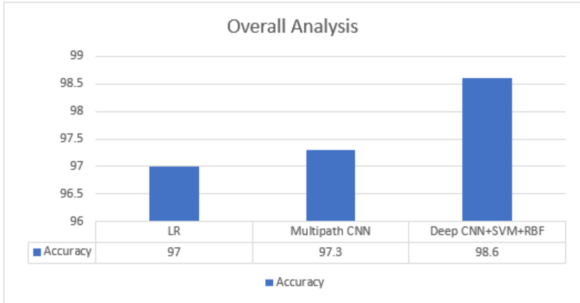

Fig 5. Overall Analysis

From this comprehensive analysis, our study analyzed the performance-based accuracy and identified that the Hybrid technique achieves better than the ML and DL techniques. Fig 4 shows the hybrid model of Deep CNN+SVM +RBF achieved the best accuracy.

4.1. Overall Summary

The Hybrid approach, which combines ML and DL, emerges as a compelling convergence of innovation and interpretability. ML algorithms excel at managing structured data and creating interpretable predictions, but DL models are proficient at learning detailed patterns and representations from unstructured data such as images. By combining ML and DL components, hybrid techniques take advantage of ML models' interpretability and DL models' feature learning capabilities, producing more robust and accurate predictions. Hybrid learning involves combining features from different sources to improve classification performance. For instance, in brain tumor detection using MRI images, hybrid approaches combine texture analysis, shape descriptors, and intensity histograms from machine learning algorithms with deep features from convolutional neural networks. This fusion of diverse representations enhances the algorithm's ability to capture a wider range of tumor characteristics and spatial relationships, enhancing discrimination between tumor and normal tissue regions. Moreover, these techniques often use transfer learning, where pre-trained deep learning models are fine-tuned for specific tasks with limited labelled data. This allows hybrid models to transfer knowledge from large-scale datasets, like image classification, to brain tumor detection tasks. This initialization accelerates learning, reduces overfitting risk, and effectively utilizes limited training data, resulting in superior performance compared to training from scratch.

Hence, the Hybrid method achieves higher accuracy, generalization across various datasets, and increased interpretability by leveraging the attribute extraction capabilities of DNN while leveraging interpretative characteristics of conventional ML techniques. This powerful framework addresses complex classification tasks, resulting in more accurate and reliable diagnostic systems in medical imaging, thanks to the synergies between different learning paradigms and opening up a new route to strengthen the accuracy and reliability of BT detection in MRI imaging.

5. Conclusion

A comparative analysis of ML, DL, and Hybrid Learning methodologies demonstrates that the synergy between machine learning and MRI imaging has significant promise. The better outcome of the Hybrid model is especially noteworthy with Deep CNN+SVM+RBF hybrid approach standing out for its exceptional accuracy, sensitivity, and specificity achieving 98.6%, 98.2%, and 98.9%. These results suggest a significant potential for the discipline, suggesting that combining different learning algorithms leads to a more effective and precise BT detection system. Moving forward, the findings of this work give useful insights that will guide future research endeavours and contribute to the continuing development of approaches at the interface of machine learning and medical imaging.

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References

Ahmad, S., & Choudhury, P. K. (2022). On the performance of deep transfer learning networks for brain tumor detection using MR images. IEEE Access, 10, 59099-59114.

Aiwale, P., & Ansari, S. (2019). Brain tumor detection using KNN, International Journal of Scientific & Engineering Research, 10(12), 187-193.

Al-Zurfi, A. N. H. (2019). An automated classification system to determine malignant grades of brain tumor (glioma) in magnetic resonance images based on meta-trainable multiple classifier schemes, University of Salford (United Kingdom).

Amin, J., Sharif, M., Haldorai, A., Yasmin, M., & Nayak, R. S. (2021). Brain tumor detection and classification using machine learning: a comprehensive survey, Complex & intelligent systems, 1-23.

Anand, L., Rane, K. P., Bewoor, L. A., Bangare, J. L., Surve, J., Raghunath, M. P., ... & Osei, B. (2022). Development of machine learning and medical-enabled multimodal for segmentation and classification of brain tumors using MRI images, Computational Intelligence and Neuroscience, 2022.

Archana, K. V., & Komarasamy, G. (2023). A novel deep learning-based brain tumor detection using the Bagging ensemble with K-nearest neighbour, Journal of Intelligent Systems, 32(1), 20220206.

Athira, V. S., Dhas, A. J., & Sreejamole, S. S. (2015). Brain tumor detection and segmentation in MR images using GLCM and AdaBoost classifier, International Journal of Engineering Research, 3, 32-36.

Avazzadeh, Z., Hassani, H., Ebadi, M. J., Agarwal, P., Poursadeghfard, M., & Naraghirad, E. (2023). Optimal approximation of fractional order brain tumor model using generalized Laguerre polynomials, Iranian journal of science, 47(2), 501-513.

Brindha, P. G., Kavinraj, M., Manivasakam, P., & Prasanth, P. (2021, February). Brain tumor detection from MRI images using deep learning techniques, In IOP conference series: materials science and engineering , 1055(1), 012115, IOP Publishing.

D. R., Dash, R., Majhi, B., & Zhang, Y. (2019). A hybrid regularized extreme learning machine for automated detection of the pathological brain, Biocybernetics and Biomedical Engineering, 39(3), 880-892.

Febrianto, D. C., Soesanti, I. and Nugroho, H. A. (2020) Convolutional Neural Network for Brain Tumor Detection, IOP Conf. Ser.: Mater. Sci. Eng., 771(1), 012031, doi: 10.1088/1757-899X/771/1/012031.

Garg, G., & Garg, R. (2021). Brain tumor detection and classification based on hybrid ensemble classifier. arXiv preprint arXiv:2101.00216.

Gurbină, M., Lascu, M., & Lascu, D. (2019, July). Tumor detection and classification of MRI brain images using different wavelet transforms and support vector machines, In 2019 42nd International Conference on Telecommunications and Signal Processing (TSP), 505-508. IEEE.

Győrfi, Á., Kovács, L., & Szilágyi, L. (2019, October). Brain tumor detection and segmentation from magnetic resonance image data using ensemble learning methods, In 2019 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp. 909-914. IEEE.

Hannan, S. A., Hivre, M., Lata, M., Krishna, B. H., Sathyasiva, S., & Arshad, M. W. (2022). Brain damage detection using Machine learning approach, International Journal of Health Sciences, Special, (7), 4910-4924.

Haq, E. U., Jianjun, H., Huarong, X., Li, K., & Weng, L. (2022). A hybrid approach based on deep CNN and machine learning classifiers for tumor segmentation and classification in brain MRI, Computational and Mathematical Methods in Medicine, 2022.

J. P. Francisco, Z. M. Mario, and R. A. Miriam, “A deep learning approach for brain tumor classification and segmentation using a multiscale convolutional neural network,” Healthcare, 9(2),153, 2021.

Jahromi, Z. F., Javeri, A., & Taha, M. F. (2019). Tumor suppressive effects of the pleiotropically acting miR-195 in colorectal cancer cells, EXCLI journal, 18, 243.

Jia, Z., & Chen, D. (2020). Brain Tumor Identification and Classification of MRI images using deep learning techniques, IEEE Access.

Jiang, S., Gu, Y., & Kumar, E. (2023). Magnetic Resonance Imaging (MRI) Brain Tumor Image Classification Based on Five Machine Learning Algorithms, Cloud Computing and Data Science, 122-133.

Kavitha, A. R., & Chellamuthu, C. (2013). Detection of brain tumor from MRI image using modified region growing and neural network, The Imaging Science Journal, 61(7), 556-567.

KKaur, P., Singh, G., & Kaur, P. (2020). Classification and validation of MRI brain tumor using optimized machine learning approach. In ICDSMLA 2019: Proceedings of the 1st International Conference on Data Science, Machine Learning and Applications, 172-189. Springer Singapore.

Krauze, A. V., Zhuge, Y., Zhao, R., Tasci, E., & Camphausen, K. (2022). AI-driven image analysis in central nervous system traditional machine learning, deep learning, and hybrid models, Journal of biotechnology and biomedicine, 5(1), 1.

Kurian, S. M., Devaraj, S. J., & Vijayan, V. P. (2021). Brain Tumour Detection by Gamma DeNoised Wavelet Segmented Entropy Classifier. Computers, Materials & Continua, 69(2).

Lah, T. T., Novak, M., & Breznik, B. (2020, February). Brain malignancies: Glioblastoma and brain metastases, In Seminars in Cancer Biology, 60, 262-273. Academic Press.

Lamrani, D., Cherradi, B., El Gannour, O., Bouqentar, M. A., & Bahatti, L. (2022). Brain tumor detection using MRI images and convolutional neural network, International Journal of Advanced Computer Science and Applications, 13(7).

Magadza, T., & Viriri, S. (2021). Deep learning for brain tumor segmentation: a survey of the state-of-the-art, Journal of Imaging, 7(2), 19.

Maqsood, S., Damaševičius, R., & Maskeliūnas, R. (2022). Multi-modal brain tumor detection using deep neural network and multiclass SVM, Medicina, 58(8), 1090.

Masood, M., Nazir, T., Nawaz, M., Mehmood, A., Rashid, J., Kwon, H. Y., & Hussain, A. (2021). A novel deep learning method for recognition and classification of brain tumors from MRI images, Diagnostics, 11(5), 744.

McFaline-Figueroa, J. R., & Lee, E. Q. (2018). Brain tumors, The American journal of medicine, 131(8), 874-882.

Noreen, N., Palaniappan, S., Qayyum, A., Ahmad, I., & Alassafi, M. O. (2021). Brain Tumor Classification Based on Fine-Tuned Models and the Ensemble Method. Computers, Materials & Continua, 67(3).

Panesar, S. S., D'Souza, R. N., Yeh, F. C., & Fernandez-Miranda, J. C. (2019). Machine learning versus logistic regression methods for 2-year mortality prognostication in a small, heterogeneous glioma database, World neurosurgery: X, 2, 100012.

Pooja, A., Shalini, D., Shiri, J. S., & Sowmiya, M. (2023). Enhancement of Brain Tumor Detection on MRI Imaging Using AlexNet, International Journal of Research in Engineering, Science and Management, 6(5), 132-134.

Pugalenthi, R., Rajakumar, M. P., Ramya, J., & Rajinikanth, V. (2019). Evaluation and classification of the brain tumor MRI using machine learning technique. Journal of Control Engineering and Applied Informatics

Ranjbarzadeh, R., Bagherian Kasgari, A., Jafarzadeh Ghoushchi, S., Anari, S., Naseri, M., & Bendechache, M. (2021). Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images, Scientific Reports, 11(1), 10930.

Saeedi, S., Rezayi, S., Keshavarz, H., & R. Niakan Kalhori, S. (2023). MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques, BMC Medical Informatics and Decision Making, 23(1), 16.

Senan, E. M., Jadhav, M. E., Rassem, T. H., Aljaloud, A. S., Mohammed, B. A., & Al-Mekhlafi, Z. G. (2022). Early diagnosis of brain tumor MRI images using hybrid techniques between deep and machine learning—computational and Mathematical Methods in Medicine, 2022.

Shaari, H., Kevrić, J., Jukić, S., Bešić, L., Jokić, D., Ahmed, N., & Rajs, V. (2021). Deep learning-based studies on pediatric brain tumors imaging: a narrative review of techniques and challenges, Brain Sciences, 11(6), 716.

T. Tazin etc., (2021) A Robust and Novel Approach for Brain Tumor Classification Using Convolutional Neural Network, Comput Intell Neurosci, 2021, 2392395, doi: 10.1155/2021/2392395.

Takei, H., Shinoda, J., Ikuta, S., Maruyama, T., Muragaki, Y., Kawasaki, T., & Iwama, T. (2019). The usefulness of positron emission tomography for differentiating gliomas according to the 2016 World Health Organization classification of tumors of the central nervous system, Journal of Neurosurgery, 133(4), 1010-1019.

Talo, M., Yildirim, O., Baloglu, U. B., Aydin, G., & Acharya, U. R. (2019). Convolutional neural networks for multi-class brain disease detection using MRI images, Computerized Medical Imaging and Graphics, 78, 101673.

Telrandhe, S. R., Pimpalkar, A., & Kendhe, A. (2016, February). Detection of brain tumors from MRI images by using segmentation & SVM, In 2016 world conference on futuristic trends in research and innovation for social welfare (Startup Conclave), 1-6, IEEE.Nayak,

Ullah, S., Ahmad, M., Anwar, S., & Khattak, M. I. (2023). An Intelligent Hybrid Approach for Brain

Tumor Detection, Pakistan Journal of Engineering and Technology, 6(1), 42-50.

Verekar, M. A. O., & Salkar, V. (2019). Detection and Classification of Brain Tumor Using Naïve Bayes and J48, International Journal of Computer Science Engineering and Information Technology Research (IJCSEITR), 9, 19-28.

Wageh, M., Amin, K. M., Zytoon, A., & Ibrahim, M. (2023). Brain Tumor Detection Based on A Combination of GLCM and LBP Features with PCA and IG. IJCI, International Journal of Computers and Information, 10(2), 43-53.

Wanis, H. A., Møller, H., Ashkan, K., & Davies, E. A. (2021). The incidence of major subtypes of primary brain tumors in adults in England 1995-2017, Neuro-Oncology, 23(8), 1371-1382.

Yildirim, M., Cengil, E., Eroglu, Y., & Cinar, A. (2023). Detection and classification of glioma, meningioma, pituitary tumor, and normal in brain magnetic resonance imaging using a deep learning-based hybrid model, Iran Journal of Computer Science, 1-10.

Yousefi, O., Azami, P., Sabahi, M., Dabecco, R., Adada, B., & Borghei-Razavi, H. (2022). Management of optic pathway glioma: a systematic review and meta-analysis, Cancers, 14(19), 4781.

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