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Systematic Review Article

A systematic review on a comparative study of AI techniques for the classification of brain tumour

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Abstract: This paper explores advances in Machine Learning (MI) techniques for detecting brain tumours using Magnetic Resonance Imaging (MRI) images. Previous research used a variety of algorithms, although there are disparities in terms of efficacy, reliability, computational complexity, and execution time. An early and exact diagnosis of brain tumours is required to improve treatment success and patient survival. This study thoroughly examines existing MI and newly invented deep learning algorithms, emphasising their performance in detecting, segmenting, and classifying tumour images. Furthermore, it examines the most recent advances in cancer grade classification and segmentation, emphasising the use of MI, digital image processing, and medical experience to increase diagnosis accuracy. Notable models, such as deep neural networks and Artificial Neural Networks (ANNs), have achieved accuracy rates of 98%, with some models nearing 99%. This study seeks to give a clear roadmap for future research in the rapidly growing field of brain tumour diagnostics, emphasizing the importance of imaging technologies such as MRI and sophisticated computational tools in early identification and treatment planning. The evaluation intends to provide a guide for further investigations in the developing field of brain tumour diagnostics.

Keywords: Magnetic resonance imaging, Artificial neural network, Softmax regression, Support vector machine, Segmentation, Genetic Algorithm, Convolutional neural network.

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1. Introduction

Previous studies used a variety of approaches; however, there were differences in effectiveness, repeatability, processing time, and computing complexity. Regarding brain tumours, a timely and precise diagnosis is crucial for better treatment success and patient survival. This research examines in detail the applicability of Machine Learning (MI) techniques and recently developed deep learning algorithms for brain cancer diagnosis, focusing on the performance of these algorithms at each stage of the process: detection, segmentation, and classification. It also discusses the latest advancements in the grading and categorization of cancer, highlighting how medical expertise, digital image processing, and MI combine to increase diagnostic accuracy. The evaluation intends to provide a guide for future studies on the emerging topic. These techniques overcome data aberrations such as low contrast, fuzzy borders, and poor spatial resolution while automating the measurement and morphology of tumours.

The study highlights the therapeutic value of a precise diagnosis of brain tumours, stressing the need for early detection and the application of imaging technologies like MRI. In addition to highlighting accomplishments, difficulties, and potential paths forward, it emphasizes the function of segmentation in the detection, segmentation, and classification stages. The proposed models also outperformed existing methods for example, assistance deep neural networks and Artificial Neural Networks (ANNs) have 98.5% accuracy rates using ANN with an average of 94.07% being achieved Softmax classifier attained 98.67% on Convolutional Neural Network (CNN) architecture, which rose to 99.12% with clustering integration Furthermore, the HDLN model obtained a multi-class brain tumour classification accuracy of 98.53% in total, outperforming multiple other methods and yielded strong precision and F1 scores overall tumour types more than 98%.

2. Literature review

More than 120 distinct kinds of brain tumours make finding an efficient treatment extremely difficult. Approximately two-thirds of primary brain tumours are benign tumours. Glioblastoma is the most prevalent type of primary malignant brain tumour. Even with intensive treatment, the average survival time is less than a year. Between 20 and 40 per cent of cancer patients will eventually develop metastatic brain tumours. As cancer patients live longer, there is a rising incidence of metastatic brain tumours. Thus, techniques must be developed for early diagnosis of brain tumours to reduce the mortality rate.

The researchers used MRI images and various tumour segmentation techniques, as well as MI algorithms, which allow computers to learn from data, predict outcomes, and adapt to changing inputs without explicit programming, recognize patterns, generalize from examples, and adapt to changing inputs have been used to categorize tumours into Grades 1–4, as well as benign or malignant. Table-1 summarizes the key findings and techniques employed by different authors over the period for the diagnosis of brain-related cancer.

Table-1: Summary of different authors' contributions

Author	Technique employed	Results
Irmak (2021)	CNN model is used, and hyperparameters have been tuned through grid search optimization.	For classification 1, accuracy was 99.3%, and AUC was 0.09995. For classification 2, accuracy was 92.55%, and AUC was 0.9881. For classification 3, accuracy was 98.14%, and AUS was 0.9994.

Raja and Rani (2020)	Used DAE, JOA, and softmax regression to categorize tumour images obtained from MRI to detect the presence of oedema and non-oedema tumours using Bayes Fuzzy clustering.	The proposed method obtained 98.5% accuracy compared to deep neural networks and artificial neural networks.
Arunkumar *et al.* (2019)	The automated segmentation and identification of brain tumours using Artificial Neural Networks (ANN) on Magnetic Resonance Imaging (MRI) images.	The ANN method yielded an accuracy of 94.07%.
Siar and Teshnehlab (2019)	A Convolutional Neural Network (CNN) used to classify brain tumours.	Among the classifiers tested in the CNN architecture, Softmax had the best accuracy, scoring 98.67%. On the test data, however, the accuracy rose to 99.12% after integrating the clustering algorithm and CNN
Gurbină *et al.* (2019)	Discussed using MRI to differentiate between healthy and tumour-affected brains (benign or malignant). Steps in the suggested technique included pre-processing and using kernel and linear techniques to train Support Vector Machines (SVMs).	High accuracy along with computational benefits.
Lamrani *et al.* (2022)	Discussed the use of classification algorithm using Machine Learning (MI). A CNN architecture comprising 5 convolutional layers was created to classify brain tumors.	This model outperforms techniques such as ANN, Random Forest, Transfer learning, and even other CNN models, obtaining a 96% accuracy rate and a 96.5% F1-Score.
Amin *et al.* (2020a)	Applied 4 layered LTSM on BRATS and SISS-ISLE datasets.	Softmax layer achieved 98% accuracy in classifying tumors as benign or malignant, and 0.95 AAC is achieved on the BRATS dataset.
Kumar *et al.* (2023)	Proposed pre-processing for local smoothing where mean filters were used to reduce noise and enhance contrast. ResNet-50 was utilised for feature extraction, which involves obtaining structural features from pre-processed MRI images.	All tumour types had precision and F1 scores exceeding 98%, and the proposed HDLN model reaches an overall multi-class brain tumour classification accuracy of 98.53%.
Seetha and Raja (2018)	Propose a technique for classifying brain tumour MRI scans that use CNN to get around issues like the uneven distribution of tumours and normal images.	The CNN achieved an accuracy of 97.5%
Kaldera *et al.* (2019)	Used T1-weighted MRI brain tumour images and concentrated on axial MRI scans, enhanced with contrast for meningioma and glioma tumours. A CNN was used to classify tumours.	The classification model for brain tumours had an average accuracy rate of 94% and 100% for meningioma detection. Verified against ground truth labels, tumour segmentation produced a 94.6% confidence interval for localization
Hemanth *et al.* (2019)	Use a CNN with a 3x3 kernel-based segmentation algorithm.	When compared to other methods, such as Genetic Algorithm (83.64%), Conditional Random Field (89%), and Support Vector Machine (84.5%), CNN performs more accurately (91%) than the others.

Çinar and Yildirim (2020)	Address the pressing need for a timely diagnosis of brain malignancies by utilizing deep learning to add and modify layers to Resnet50.	The half-breed model accomplishes a high exactness pace of 97.2%
Naser *et al.* (2020)	Utilize profound figuring out how to rapidly analyse cerebrum malignant growths involving CNN for cancer division and Vgg16 for cancer reviewing.	For tumour identification, the segmentation method achieves a mean dice similarity coefficient of 0.84 and an accuracy of 0.92.
Sun *et al.* (2019)	Present a deep learning system for classifying brain tumours and predicting their survival based on multimodal MRI data. Growth subregion division is improved when three convolutional brain networks are consolidated.	The study plans to investigate various network topologies and feature selection strategies in the future and reports a survival prediction accuracy rate of 61.0%.
Saba *et al.* (2020)	Proposed a method that combines an optimized Transfer learning model (VGG-19) with the grab-cut technique for accurate lesion-symptom identification	Classifiers are fed the generated fused vector. Impressive results were obtained from testing on well-known medical databases (BRATS 2015, 2016, and 2017). For BRATS 2015 and 2017, the Dice Similarity Coefficients (DSC) were very high at 0.99 and for BRATS 2016, the score was perfect at 1.00.
Kaifi (2023)	Grad-CAM with ResNet50 for explainable AI in MRI-based brain tumour detection.	The study utilized Grad-CAM integrated with ResNet50 to highlight regions of MRI scans influencing the model's predictions, enhancing clinical interpretability. Preprocessing involved intensity normalization, artefact correction, and image augmentation for dataset uniformity. The proposed model achieved a classification accuracy of 98.5% with enhanced transparency and robustness compared to traditional CNN models
Kang *et al.* (2021)	Ensemble learning using pre-trained networks such as DenseNet-169 and MI classifiers like SVM with RBF kernels.	This ensemble model applied transfer learning for MRI brain tumour classification. It achieved an accuracy of 97.6% on multi-class datasets and proved effective in identifying high-grade gliomas with specificity exceeding 95%. The inclusion of multiple network features improved generalizability across diverse datasets.
Zhang *et al.* (2021)	GAN-based feature fusion for cross-modality MRI tumour segmentation.	The approach utilized GANs for synthesizing cross-modality features and achieved a Dice score of 0.886 on the BraTS dataset. By integrating complementary features from multiple MRI modalities, the model demonstrated improved segmentation accuracy and tumour localization.

Gupta and Sharma (2023)	Multi-task learning framework for tumour classification and survival prediction.	The model leveraged shared feature extraction layers by combining classification and survival analysis tasks. The framework reported an accuracy of 97.5% for tumour classification and a mean squared error of 0.03 for survival prediction across diverse MRI datasets.

3. Methods and materials

Irmak *et al.* (2021) used a Convolutional Neural Network (CNN) model where hyperparameters were tuned through grid search optimization. Four datasets namely RIDER, REMBRANDT, TCGA-LGG, and T1 weighted images, and three assimilation tasks were performed. CNN model was used for classification. CNN is a type of neural network used to process and analyse visual input such as photos and video. The softmax layer is used to predict the presence of tumour and tumour grade. Grid search optimization is performed to make it computationally less expensive and for tuning important hyperparameters, the dataset divided into 60:20:20 ratio of training, validation and testing datasets respectively is used by the grid search optimization in different combinations to yield higher accuracy.

Raja and Rani (2020) combined DAE, JOA and softmax regression, a generalization of logistic regression that allows for multi-class classification is used for the categorization of tumour images obtained from MRI to detect the presence of oedema and non-edema tumours using Bayes Fuzzy clustering to make segments of the tumour images by grouping pixels based on statistical and fuzzy criteria. BRATS images containing HGG as well as LGG, the following process using MATLAB has been performed:

- Pre-processing.
- BFC-based segmentation.
- Robust extraction of features.

WPTE includes Discrete Wavelet packet Transform that provides time-frequency representation and Tsalttias entropy for evaluating complexities and scattering transform, the final step was tumour classification where an encoder capable of producing sensitive power was named Deep Autoencoder Network. Softmax regression was used as it can take many values at a single time and will help the multilayer stack of DAE in classification as DAE.

Arunkumar *et al*. (2019) focused on improving, the automated segmentation and identification of brain tumours using Artificial Neural Networks (ANN) on MRI images Artificial Neural Networks (ANNs) are computer models inspired by biological neural networks in the human brain that are used in MI for tasks such as pattern recognition, classification, regression, and decision-making. Assessment is done using the BRATS benchmark dataset. Distances between pixels and cluster centres are chosen. In the next stage, neural networks extract features and choose pertinent cases of brain tumours. Texture features have been used to identify areas in MRI images. Scaling values for classification and pixel colour representations are involved in testing. An ANN-based method is suggested to automate brain tumour segmentation. Region growing is used for image segmentation. When it came to image texture feature analysis, the neural network classifier outperformed the SVM classifier by a significant margin in the tumour classification evaluation. Badža and Barjaktarović (2020) used a T1 MRI image dataset that contained three planes and three types of tumours. In the pre-processing process, images were notarized and transformed into vertical and horizontal planes, with 22 layers. Siar *et al.* (2019) used a CNN (Convolutional Neural Network) to classify brain tumours. This study was performed on a dataset that included 153 patients' brain MRI pictures, both with and without brain tumours. A Rectified Linear Unit (ReLU), which introduces non-linearity by outputting the input directly with convolutional, sub-sampling, normalization, and fully connected layers, was used for image classification.

Gurbină *et al.* (2019) have discussed the use of MRI to differentiate between healthy and tumour-affected brains (benign or malignant). Steps in the suggested technique included pre-processing and using kernel and linear techniques to train SVMs. MRI brain image denoising using various wavelet families (Hara, Symlet, Morlet, and Daubechies) and evaluating their performance using metrics (SNR, PSNR, and MSE) is the main goal of the pre-processing step, the best performance is shown by Haar. In segmentation, pixels are thresholded and divided into object and background classes. Various wavelet levels are utilized, particularly with CWT, which preserves edges during segmentation to achieve high accuracy.

Lamrani *et al*. (2022) discussed using classification algorithm by using MI. A CNN architecture comprising 5 convolutional layers was created to classify brain tumors. Strategies such as data augmentation, dropout, batch normalization, and pooling were used to avoid overfitting. The optimization of the neural network's performance was emphasized by highlighting the Loss Function. The CNN model was trained using Google Colab, a Tesla K80 GPU, an Intel Xeon processor, and thirteen gigabytes of RAM. The model didn't exhibit overfitting.

Amin *et al*. (2020a) used the BRATS and SISS-ISLE datasets to analyse brain tumours using a 4-layered LSTM model. Pre-processing procedures for the datasets included smoothing for noise reduction and bias field correction to address intensity inhomogeneities brought on by coil variations in the magnetic field. Starting with an input layer, the approach used an 8-layer architecture for improved image feature extraction. A combination of HU values was supplied to the LSTM layers to improve accuracy, and features calculated by the LSTM layers were given to the softmax layer to create probability distributions. After computing features by the LSTM layer, they are passed to the softmax layer to obtain a probability combination of HU has been given to LSTM layers because it directly affects the accuracy. Although the strategy seems promising, the report leaves out important aspects of the methodology. The absence of information regarding the datasets' size, diversity, and possible class imbalances limits how broadly the results may be applied. Reproducibility is hampered by the lack of specification of the hardware, software, and tool configurations required for implementation. Additionally, it is unclear what criteria would be used to evaluate performance and compare it to other models. Furthermore, issues like overfitting, computational demands, and possible restrictions on clinical applicability are not discussed. No broader factors are considered, such as data biases and the moral ramifications of using the model in practical situations. Adding these specifics would increase the study's effect, dependability, and transparency.

Kumar *et al*. (2023) proposed pre-processing for local smoothing where mean filters were used to reduce noise and enhance contrast. ResNet-50 a deep residual network with 50 layers was utilised for feature extraction, which involves obtaining structural features from pre-processed MRI images. Mask RCNN was utilised for pixel-level segmentation and object detection, enabling accurate classification of various brain tumour types. SE-ResNet was used to segment brain tumours efficiently by examining the dependencies between the channels of convolutional features. Seetha and Raja (2018) propose a technique for classifying brain tumour MRI scans that use CNNs to get around issues like the uneven distribution of tumours and normal images. The methodology included:

- Pre-processing
- Feature extraction
- Convolutional Neural Network
  a. Applying CNN to first layer
  b. Applying smoothing filter
  c. Applying Rectified Linear Unit
  d. Adding loss layer

Improving diagnosis and therapy aims to offer precise and effective segmentation and classification. Abd-Ellah *et al* (2019 created a deep learning system that operates on many scales, enabling the automated identification and classification of brain tumours from MRI pictures. Rehman *et al*. (2021) research employs a 3D Convolutional Neural Network to eliminate tumours using pre-trained CNN models to extract characteristics. For precise classification, the approach makes use of a feedforward neural network and a correlation-based selection procedure.

Mohan *et al*. (2018) used the degree prediction method of Support Vector Machine (SVM), which is effective for complex, non-linear border classification tasks. Norhashimah *et al.* used Convolutional Neural Networks (CNNs) to classify brain lesions in MRI images. To improve accuracy and resilience, ensemble learning techniques including stacking and boosting were suggested. The dimensions of the issue and the characteristics of the dataset may have distinct effects on the effectiveness of each solution. These two experiments highlight the limitations of existing machine-learning methods. This combined review process exposes key insights into brain MR image segmentation and classification, focusing on the timely detection and grading of brain tumours. But the study finds they fall short in specific ways: For example, while most have high classification accuracy, many simply separate tumours into large groups-for instance malignant versus benign or low-grade and high-grade cancers rather than more precise subtypes. Detailed classification like the WHO grading system is not emphasized. The review argued that imaging and MI strategies be developed explicitly for more refined grading, with common but challenging gliomas such as astrocytomas.

Kaldera *et al*. (2019) used T1-weighted MRI brain tumour images and concentrated on axial MRI scans that were enhanced with contrast for meningioma and glioma tumours. Classifying tumours used a CNN that employs two convolutional layers with max-pooling and ReLU activation after down sampling images to 128x128 pixels. A Faster R-CNN model was used for tumour segmentation, producing region suggestions for localization. Bounding box regions were subjected to edge detection algorithms, namely Prewitt and Sobel, to detect tumour boundaries precisely. This method combined edge detection and deep learning techniques to identify and locate brain tumours in MRI images precisely. And patterns found in actual MRI data.

Zhang *et al*. (2021) performed multi-modality MRI data-driven brain tumour segmentation, and a novel cross-modality deep feature learning technique has been devised. The technique consists of two processes: a GAN-based learning scheme-based Cross-Modality Feature Transition (CMFT) process and a Cross-Modality Feature Fusion (CMFF) process for efficient feature integration. The evaluation beats baseline models and state-of-the-art techniques in segmentation performance when assessed against BraTS benchmarks. In the BraTS 2018 training set, the average Dice score is 0.886, which is somewhat higher than the Dice score on the BraTS 2018 validation set. The suggested approach performs better than ensemble and single-prediction techniques in terms of Hausdorff Distance, Sensitivity, and Dice score. The study's limitations include the need for comparable network topologies and the possibility of future advancements through knowledge distillation techniques.

Hemanth *et al.* (2019) use a CNN with a 3x3 kernel-based segmentation algorithm. The method comprised of the following steps:

- Pre-processing
- Average filtering
- Pixel-based segmentation

When compared to other methods such as Genetic Algorithm (83.64%), Conditional Random Field (89%), and Support Vector Machine (84.5%), CNN performs more accurately (91%) than the others.

Shakeel *et al.* (2019) highlight the necessity of achieving low false negatives in the context of detecting brain tumours. They implemented an FDA and BPNN-based computer-aided diagnosis system that can locate tumours as small as 3mm. Also, the study used near-infrared imaging technology and wireless sensor networks for better detection. For tumour segmentation, the MI based BPNN was preferable to the Adaboost Classifier which proved beneficial when handling complicated cases. The methodology, on the other hand, is ineffective in portraying the key elements of the research, including the materials, methods, tools and data used, analysis criteria, and challenges experienced during the study. There are not many specifics regarding the dataset used for the research like the number of samples, the source of the samples and the variety of the samples which puts the results into question as to whether they can be generalized. The paper does not mention which tools or hardware setups were used which are important for replication of the study. Also, while the comparison focuses on the superiority of the BPNN, there is no clarity on the performance gap with the Adaboost Classifier. They do not seem to be exhaustive in going into possible limitations such as computational load, data pre-processing, or real-world implementation concerns.

Hussain *et al.* (2019) propose an approach that is more accurate for extracting multimodal characteristics using MI algorithms to identify brain tumours. To extract several highlights, such as textural, morphological, entropy-based, Filter, and EFDs, a data set including images of the development of the cerebrum was used. When using morphological, texture, SIFT, and entropy data, Naive Bayes and Decision Trees displayed the highest detection accuracy. This was the case. It is clear from the results that Innocent Bayes is the most effective classifier for mind development ID when certain limits are considered.

Çinar and Yildirim (2020) widen the scope of early detection of brain malignant tumours through deep learning by modifying the ResNet50 architecture by adding more layers. Their hybrid model's accuracy rate is 97.2% which is higher than most contemporary architectures and it holds quite a bit of promise for image classification of brain tumors in computer-aided detection systems. However, it contains some methodological shortcomings, many of which are key to the deep understanding and replication of the research. Regarding the datasets, the specific dataset used, its size, diversity and source are presented too generally, raising questions about the scope of the obtained results. In addition, information about the tools and software used as well as hardware parameters is vague. As much as the results reveal the model as effective, there are no clear criteria for evaluating it and comparing it with other architectures. Problems experienced during training such as overfitting and even computational costs or dataset imbalance have not been addressed, nor have the potential restrictions of this model in real-life settings. There seem to be no ethical perspectives, or research taboos present that concern data biases or even the broader picture of AI as a medical diagnostic tool.

Naser *et al.* (2020) utilize profound figuring out how to rapidly analyse cerebrum malignant growths involving CNN for cancer division and Vgg16 for cancer reviewing. For tumour identification, the segmentation method achieves a mean dice similarity coefficient of 0.84 and an accuracy of 0.92. For the classification of lower-grade gliomas, the grading model has similar accuracy, sensitivity, and specificity scores. This strategy demonstrates the potential for automated, non-invasive tumour segmentation and grading in clinical settings and is useful for LGG diagnosis and treatment planning. Kang *et al*. (2021) suggest that a set of deep characteristics and MI classifiers based on transfer learning are used in the study's method for detecting brain tumours. A careful investigation utilizing nine classifiers and thirteen pre-prepared networks on large datasets shows the group's superb exhibition, particularly while utilizing DenseNet-169, Initiation V3, and ResNeXt-50 elements. The SVM with Radial Basis Function (RBF) kernel consistently performs better than other classifiers indicating that the proposed method is effective for MRI-based brain tumour classification.

Sun *et al*. (2019) presents a deep learning system for classifying brain tumours and predicting their survival based on multimodal MRI data. Growth subregion division is improved when three convolutional brain networks are consolidated. Choice tree and arbitrary woods relapse models are utilized to anticipate endurance utilizing radio mic qualities and clinical information. The study plans to investigate various network topologies and feature selection strategies in the future and reports a survival prediction accuracy rate of 61.0%. Although the presented framework for predicting glioma survival by MRI and radiology and clinical features, displays some promise; it suffers from under-segmentation, effect size, a limited sample, and current features' incomplete explanatory power. In the future, we plan to pursue improvements with another network archetype, new feature variations, and an optimal subset of features. Khan *et al.* (2020) developed a computerised framework for mind development grouping. This framework makes use of powerful element selection and deep learning approaches. This system makes use of several different learning methods, including linear contrast stretching, Corr entropy-based joint learning, VGG16 and VGG19 transfer learning, and ELM classification. The approach displayed a high level of accuracy when applied to the BRATS datasets, which led to a quicker calculation as well as findings that were more accurate and dependable.

The authors Amin *et al*. (2020b) suggests a combination of four X-ray successions and a CNN to determine the sequence of malignant development in the cerebrum. Consolidating underlying and surface information is the responsibility of the Daubechies wavelet component, while the PDDF is responsible for removing clamour. Growth division and order may be achieved by the use of the CNN model with global thresholding. Furthermore, the technique outperforms solo sequences when used in many datasets. Despite being novel, this technique is unclear in several crucial areas that are required for thorough comprehension and replication. The authors suggest using a CNN in conjunction with four X-ray scans to identify the brain's cancerous growth sequence. They combine surface and structural data using the Daubechies wavelet component and remove noise using the PDDF approach. A CNN model combined with global thresholding is used to achieve growth segmentation and classification, and the strategy performs better than utilising single sequences on various datasets.

Saba *et al*. (2020) proposed a method that combines an optimized Transfer learning model (VGG-19) with the grab-cut technique for accurate lesion-symptom identification. The model combines texture and form, two manually created features, and optimises them using entropy for accurate and effective categorisation. When tested on well-known medical databases like BRATS 2015, 2016, and 2017, the fused feature vector is fed into classifiers and produces remarkable results on well-known medical databases (BRATS 2015, 2016, and 2017). However, certain crucial components of the process are not adequately described. There are concerns regarding generalisability because, for example, although the datasets are named, the size, variety, and precise preparation procedures are not described. Reproducibility may be hampered by the lack of a detailed description of the hardware, software, and tool configurations utilised to construct the model. This model combines two manually crafted features (texture and shape) and uses entropy to optimize them for quick and precise classification. Classifiers are fed the generated fused vector.

The purpose of the research done by Mehrotra *et al*.(2020) is to discuss a deep learning strategy that employs transfer learning to categorise brain tumours based on MRI data. This strategy strongly emphasizes distinguishing between benign and malignant forms of cerebrum cancer. The model can make use of pre-prepared deep learning networks thanks to the use of transfer learning, which significantly improves the accuracy and competence of the characterization. This approach is particularly important for exact determination, which is essential for determining the appropriate treatment strategy. This review aims to fill the gap in achieving faster and more accurate brain growth grouping by combining advanced Artificial Intelligence (AI) algorithms with unique datasets. By improving the precision with which tumour types are diagnosed, the strategy that has been developed has the potential to have a substantial impact on the planning of therapy. Patients may have access to more individualized and effective treatment choices due to the enhanced capacity to discern between benign and malignant tumours. However, the shortcomings are a limited dataset and long training periods (GoogLeNet + ADAM can be up to 112 minutes). Such gaps are envisioned to be looked upon in future research works using larger datasets and more powerful processors to enhance accuracy along with efficiency.

A contemporary AI technology that is supposed to operate on the prediction and inspection of brain tumours is discussed in research done by Ramesh *et al*. (2023). To begin, Gaussian smoothing is used to enhance the quality of X-ray pictures by reducing the presence of artifacts. This is accomplished via clearer subsequent exams. Following that, Genetic Algorithms are used to optimise the selection of features, which ultimately increases the features' capacity to differentiate between their respective processed pictures. It is essential to have this information to segment and characterise brain tumours accurately. Following the underlying handling processes, the archive presents a nuanced explanation of the utilisation of Profound deep Learning-Based Division to define development limitations exactly, which is essential for precise determination. Local Binary Patterns (LBP) are used to extract precise surface features from the growths. These highlights are then arranged in a certain order by using the K-Closest Neighbours (KNN) technique. In addition to ensuring that power is maintained during the placement cycle, this multi-step strategy also improves tumor categorization accuracy, which ultimately helps with treatment planning.

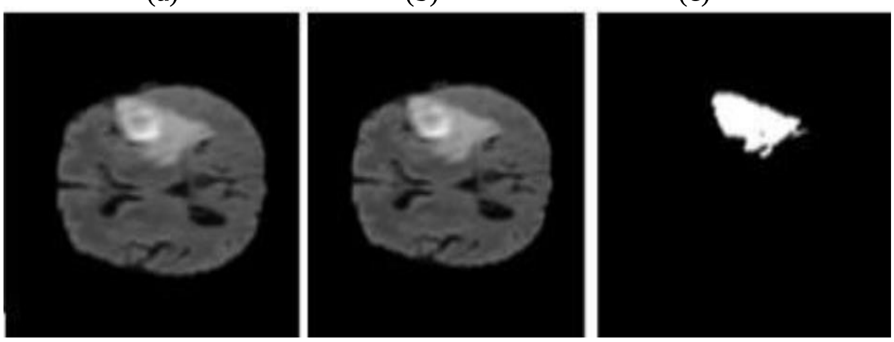
Using AI approaches, the research study by Manaswi and Sankarababu (2021) presents a flexible method for detecting and categorising brain tumours, with a particular emphasis on ML computations. Methods such as SVM, Fuzzy Clustering Means (FCM), and ANN are used to partition and extract significant data from brain MRI pictures. With the help of these high-level computational methodologies, the accuracy of brain tumour identification will be improved, which is critical for early disease detection and effective treatment development. The fundamental challenge that is tackled in this study is the exact segmentation of brain tumours using MRI images. This involves distinguishing between different kinds of brain tissues, such as Cerebrospinal Fluid (CSL), White Matter (WM), and Grey Matter (GM). The use of mechanised computer-based intelligence approaches is essential for working on analytical exactness and dependability since traditional manual analysis strategies are prone to faults. As a result, the use of these methods is essential. By implementing these simulated intelligence approaches, the archive intends to provide neuro-oncologists with extra precise instruments for diagnosing brain tumours, ultimately leading to improved silent administration and treatment outcomes. Thus, this study focuses on the AI techniques i.e. SVM, FCM and ANN that can be employed to enhance cancerous brain tumour detection as well as tumour segmentation from MRI images for a timely diagnosis process of treatment. The results of this study are somewhat difficult to interpret because it processes individual brain tissues within fine-tuning limits and involves complex computational steps that may not be applicable for routine clinical use.

4. Results

Irmak *et al*. (2021) made use of a CNN model in which for classification 1, accuracy was 99.3% and AUC was 0.09995, for classification 2, accuracy was 92.55% and AUC was 0.9881, for classification 3, accuracy was 98.14% and AUS was 0.9994. As there is multi-classification and up to 25 layers and a single layer takes a lot of time to get trained and tested, it is a time-consuming process and would not be good for use in clinical settings. Compared with existing CNN models, the proposed CNN model, which are already trained, showed better results due to the optimization of the hyperparameters. The proposed method obtained 98.5% accuracy compared to Deep Neural Networks and ANN. This accuracy can further be improved if more than one classifier is used. Combining JOA, DAE and softmax regression improved sensitivity and provided a lower error rate. The fragmentation yield of brain MRI is shown in Figure 1.

Figure 1: Brain MRI Outputs (a) Input of brain image, (b) Noise detached brain MRI, and (c) Fragmented yield of Brain MRI

(a) (b) (c)



Source: Raja and Rani (2020)

Arunkumar *et al*. (2019) focused on improving the automated segmentation and identification of brain tumours using the ANN method yielding an accuracy of 94.07%. Because brain tumours can take many different forms, sizes, and locations, automated segmentation of these tumours is a challenging task. Constraints that impact the automated systems' effectiveness result from a dataset that only includes a small number of cases of abnormal and normal brain tumours. Badža *et al.* (2020) used a T1 MRI image dataset that contained three planes and three types of tumours. For training the dataset in the training network record-based cross-validation and subject-wise cross-validation were used as two different approaches. The Glorot analyser was to initialize the weight of the convolutional layer, whereas an Adam optimizer was used for training. Speed was fast which equalled 15 ms/image, for record-wise cross-validation accuracy, was recorded to be 96.56% which was higher than subject-wise cross-validation which was 88.84%. Data was not extensive, and low subject-wise cross-validation accuracy was obtained, as the dataset was not large, and several patients remained the same by only increasing images by augmentation. It couldn't detect meningioma with high accuracy and sensitivity.

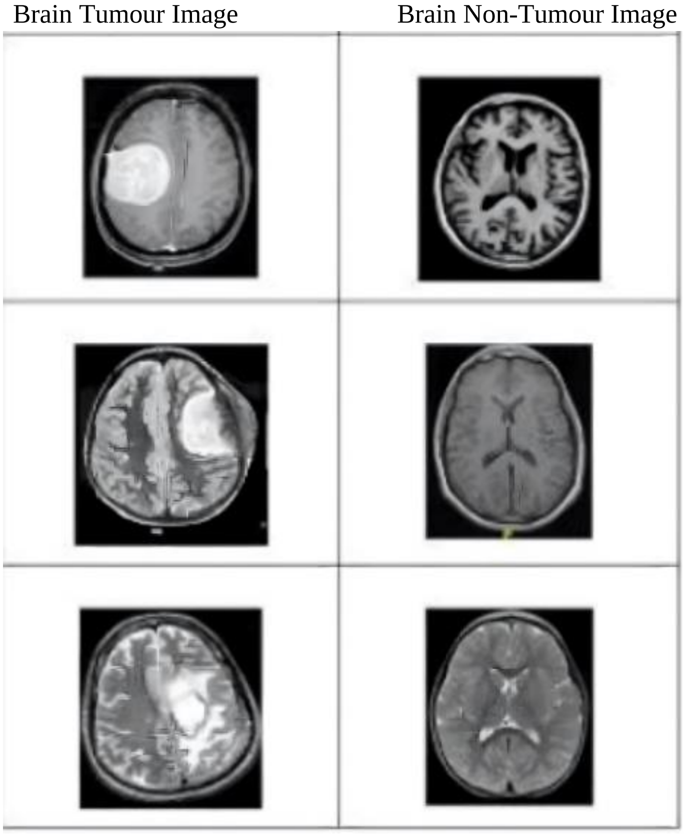
Siar *et al.* (2019) used the classifiers tested in the CNN architecture, Softmax had the best accuracy, scoring 98.67%. However, the test data's accuracy rose to 99.12% after integrating the clustering algorithm and CNN (CNN SoftMax). Medical image labelling can be difficult and error-prone, particularly in complicated cases where there may be minute distinctions between normal and abnormal images. Furthermore, due to its reliance on standardized, high-quality imaging data, the method may not be as applicable to a wide range of datasets gathered from various sources. CNN and feature extraction via clustering greatly improved the network's ability to recognize brain tumours in MRI pictures.

Gurbină *et al*. (2019) use SVMs that result in five times faster results (22 ms vs. 110 ms) when compared to other techniques. Even though they are frequently used, standard MRI sequences are not always accurate in diagnosing brain tumours, particularly different types of tumours and assessing levels of malignancy. Lamrani *et al.* (2022) use a model that outperforms techniques such as ANN, Random Forest, Transfer learning, and even other CNN models, obtaining a 96% accuracy rate and a 96.5% F1-Score. Achieving high accuracy rates does not imply that the model is excellent. Although the model's training on Google Colab with GPU support is advantageous, running such models in actual clinical environments may require substantial computational resources. Softmax layer classified the tumour as benign or malignant, 98 per cent accuracy is achieved, and 0.95 AAC is achieved on the BRATS dataset by Amin *et al.* (2020). It is not yet able to classify sub-tumour regions and thus is unable to detect the severity of the tumour. The testing time is less therefore the model is effective. However, it is assessed on MICCAI and SISS-ISLE datasets, and temporal data processing is better learned.

To ascertain the effectiveness of the proposed model, Kumar *et al*. (2023) use MRI images for testing. All tumour types had precision and F1 scores exceeding 98%, and the proposed HDLN model reaches an overall multi-class brain tumour classification accuracy of 98.53%. With improved segmentation and classification capabilities, this bridged the diagnostic gap and performed better than the previous models, exhibiting notable gains in accuracy and precision. The CNN-based categorized results are shown in Figure 2.

The CNN achieved an accuracy of 97.5% with low complexity but still, the study is deficient in areas like processing time reduction and model efficiency improvement. Investigating cutting-edge deep learning architectures and optimization techniques may be able to assist with these problems.

Figure 2: CNN based classified results

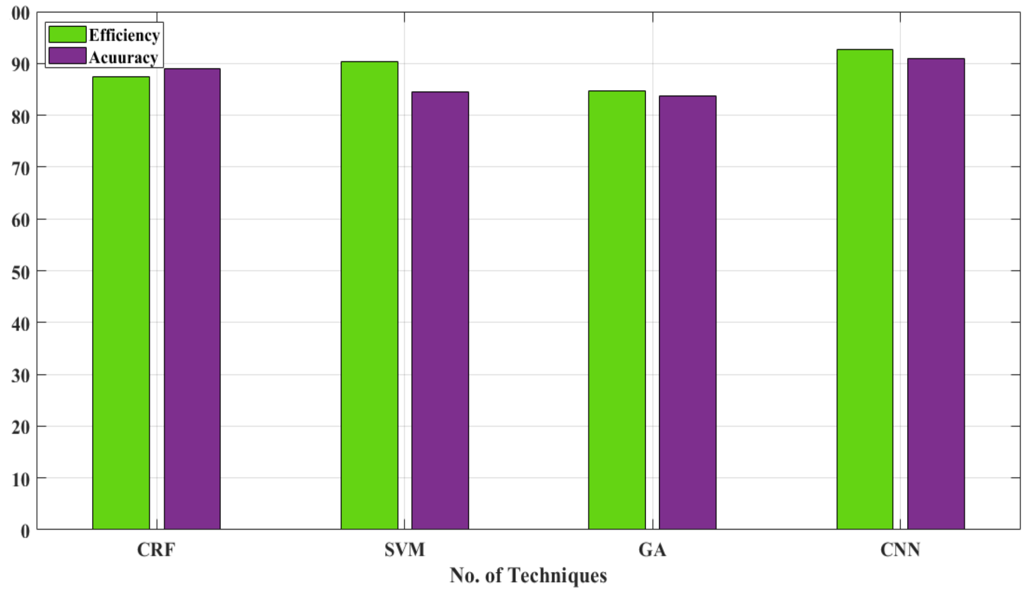


Source: Seetha and Raja (2018)

Abd-Ellah *et al*. (2019) use Deep learning methods that have a large processing overhead and limited generalizability, which provide issues despite their 93.56% accuracy and 0.876 Dice value in tumour classification, demonstrating strong performance, despite these advantages, the system suffers from high processing overhead and limited generalizability, illustrating the need for additional development to make it more effective and broadly useful. Rehman *et al*. (2021) worked on the 2015, 2017 and 2018 BraTS datasets, the approach gets accuracy scores of 98.32%, 96.97%, and 92.67%. The work improves classification accuracy and successfully tackles issues in tumour areas with low contrast. There are a few drawbacks to the strategy, though. Later improvements might focus on optimizing the model's computational aspects. The classification model for brain tumours had an average accuracy rate of 94%, and 100% for meningioma detection. Verified against ground truth labels, tumour segmentation produced a 94.6% confidence interval for localization. Future work aims to extend the approach to T2-weighted and Flair-weighted MR images for wider diagnostic support. The study finds an anomaly in the automated identification of brain tumours in MRI pictures, especially when it comes to managing artefacts caused by bone structures. Even though the accuracy was high, further study is required to solve artefact-related issues and extend the methodology to various MRI modalities and planes.

Hemanth *et al*. (2019) use a CNN with a 3x3 kernel-based segmentation algorithm. A comparison between multiple classification algorithms is shown in Fig 3. The simulation findings show that high-quality pictures can identify brain tumours. Notwithstanding, constraints could encompass susceptibility to fine-tuning parameters and possible difficulties in managing heterogeneous datasets. While the CNN-based approach presents a viable means of accurately and efficiently detecting brain tumours, more testing on more extensive and varied datasets is advised. Saba *et al*. (2020) proposed a method that combines an optimized Transfer learning model (VGG-19 For BRATS 2015 and 2017, the Dice Similarity Coefficients (DSC) were very high at 0.99, and for BRATS 2016, the score was perfect at 1.00. This method is computationally expensive and may not be suitable for clinical settings.

Figure 3: Comparison between multiple classification algorithms



Source: Hemanth *et al.* (2019)

5. Discussion

A systematic review is presented in this paper that aims to describe the remarkable developments of Artificial Intelligence (AI) techniques, especially Machine Learning (ML) and Deep Learning (DL) for the classification of brain tumours using MRI images. These innovations continue to play a vital role in improving diagnostic accuracy necessary for early treatment and better patient outcomes. In addition to the remarkable accuracy rates attained by several models, one of the more intriguing aspects of the review is that they detect false positives in context. CNN and other deep learning architectures have an accuracy of up to 99.12%.

Pre-processing techniques like noise reduction, image normalization, and data augmentation are also highlighted in the review for improving performance. These steps are essential in alleviating frequently occurring imperfections in MRI images like low contrast & blurred tumor edge which would be highly detrimental to the classification process. In particular, the incorporation of data augmentation techniques has emerged as a practical approach to improve the robustness of models and enable them to generalize better to data they have not encountered before.

This review of deep learning models applied to the clinical domain has elucidated several issues. Model training can also seem infeasible due to the computational complexity involved; models can take a long time to train or demand significant resources. In future studies, maximizing the algorithms to save time without compromising the high accuracy is highly feasible. It can be seen that variation in datasets used across the studies (e.g., data from 1 institution vs. reproducible public data) can make the stability and reproducibility of these ML models non-universal, as ML models will perform depending on the type and nature of the data from various institutions.

The review also emphasizes the importance of more differentiated tumour grading and characterization since most existing models identify high-level classifications but do not help to identify the specific pathology subtypes. The classification systems should be directly correlated with existing institutions' recognized medical grading systems (e.g., WHO classification for tumours) for refinement in future studies.

6. Conclusion

Several notable advances and insights have come from thoroughly evaluating existing research on Machine Learning (MI) and deep learning algorithms for identifying brain tumours using Magnetic Resonance Imaging (MRI) data. The findings highlight the growing effectiveness of Convolutional Neural Networks (CNNs) and other Artificial Intelligence (AI) algorithms in properly recognizing, segmenting, and categorizing brain tumours from MRI data. These technologies have surmounted classic problems such as unclear tumour borders and low picture contrast, attaining amazing accuracy rates of up to 99.12% in some cases. This level of accuracy not only increases diagnostic reliability but also improves treatment planning and patient outcomes by allowing for tumour identification and characterization early on. However, the area continues encountering hurdles like computational complexity, dataset variability, and the necessity for reliable real-world deployments. While this progress is positive, there are some issues to address. Computational complexity can be a hindrance to using it in real-time, and dataset variability can lead to low generalizability of the models. A still major concern is the reliable deployment of this in clinical settings. Addressing these challenges will catalyse the continued improvement of algorithms and datasets, as well as facilitate multi-modal imaging to further increase diagnostic performance in future studies.

Innovative AI-enabled diagnostic methods have the power to change the entire landscape of brain tumour diagnosis and management. Using these technologies in the future will overcome existing challenges and be much more precise, effective, and tailored to individual patients, enhancing patient outcomes. By addressing current limitations and continuing to innovate, these technologies promise to deliver more accurate, efficient, and personalized treatment options, significantly benefiting patient outcomes. Research should focus on improving algorithms, increasing datasets, and incorporating multi-modal imaging to enhance the clinical usability and reliability of AI-driven diagnostic tools in neuro-oncology. In conclusion, while tremendous progress has been made, further breakthroughs in AI technology show promise for revolutionizing brain tumour diagnoses, providing patients with more accurate, efficient, and personalized therapy.

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