

Evaluation Effectiveness of Brain Tumors Detection using Deep Learning: A Comparative Analysis

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Abstract: An important health issue in India is brain tumor, which add to the nation's overall cancer burden. The number of cases of brain tumors rising from last decades so research on this issue is important for improving timely diagnosis, treatment and patient health. Latest technologies such as Deep Learning (DL) shows significant potential for detecting brain tumors at early stage. This surpassing traditional diagnostic methods and helps healthcare professionals for detection of brain tumors at early stages. In this paper we perform comparative analysis of Brain tumors detection using machine learning (ML) and Deep learning. DL model such as Convolutional neural network (CNN), VGG19, ResNetV2, DenseNet121 were used to train the model.

Introduction: Unusual cell growth in the brain or central spinal canal is called a brain tumors. The two main categories of these tumors are benign and malignant. Malignant cells are cancerous, however benign ones are not. Malignant tumors can be aggressive, spreading to other sections of the brain and possibly compromising general health, whereas benign tumors typically develop slowly and do not infect neighbouring tissues. A primary brain tumor is a kind of tumor that doesn't spread from other regions of the body; instead, it starts in the brain or adjacent tissues. Different brain cell types can give rise to secondary brain tumors, which can then be categorized according to the cell of origin. Brain tumors, which impact millions of people annually worldwide, pose a serious problem in the fields of neurology and oncology. Effective treatment and better patient outcomes depend on their early discovery and precise diagnosis. The diagnosis of brain tumors has historically mostly depended on invasive techniques and expert interpretations of medical imaging. But new developments in machine learning (ML) have brought forward creative strategies that could change this environment.

Objectives: To study and analyze the various techniques for the Brain Tumor disease prediction using neural network. Data preprocessing of selected dataset. (Normalization and gray scaling). Comparative Analysis of the existing system to access effectiveness and efficiency of proposed model. Use classification techniques using deep learning algorithm and develop a model. Performance analysis using evaluation metric.

Methods: In the realm of medical imaging, deep learning has emerged as a powerful instrument, particularly for detecting and classifying brain cancers. DL models have demonstrated greater accuracy in diagnosing brain tumors through MRI scans. Various types of brain tumors, including gliomas, meningiomas, and pituitary tumors, can also be diagnosed using deep learning models. In the first phase of model building we collect the dataset from different sources. This dataset include MRI scan images from different radiologist. After that we pre-process the dataset such as resize the images, rotate the images and convert the images into grayscale image. We should remove the noise from the images to extract the features. We use high pass filtering, low pass filtering, Gaussian filters

to remove the noise from the images. Different types of features we can extract from the dataset such as shape based features, intensity based features and model based features. In the next phase we perform classification of the images using CNN, ANN, autoencoder models. In this phase we can classify the images into healthy image and tumour image.

Results: A comparative study of the literature review conducted by several writers is presented

Conclusions: DL has emerged as a powerful model, particularly for the detection and classification of brain tumors. In this paper we discuss about detail comparative analysis of DL model used for brain tumors detection.

Keywords: Machine learning (ML), Deep learning (DL), Convolutional neural network (CNN), Magnetic resonance imaging(MRI).

1. Introduction

Unusual cell growth in the brain or central spinal canal is called a brain tumors. The two main categories of these tumors are benign and malignant. Malignant cells are cancerous, however benign ones are not. Malignant tumors can be aggressive, spreading to other sections of the brain and possibly compromising general health, whereas benign tumors typically develop slowly and do not infect neighbouring tissues. A primary brain tumor is a kind of tumor that doesn't spread from other regions of the body; instead, it starts in the brain or adjacent tissues. Different brain cell types can give rise to secondary brain tumors, which can then be categorized according to the cell of origin. Brain tumors, which impact millions of people annually worldwide, pose a serious problem in the fields of neurology and oncology. Effective treatment and better patient outcomes depend on their early discovery and precise diagnosis. The diagnosis of brain tumors has historically mostly depended on invasive techniques and expert interpretations of medical imaging. But new developments in machine learning (ML) have brought forward creative strategies that could change this environment.

Algorithms are used in machine learning, a branch of artificial intelligence, to evaluate enormous volumes of data, spot trends, and provide predictions. Researchers and medical professionals can create models that improve the accuracy and speed of brain tumor diagnosis by utilizing machine learning. These models are capable of processing intricate imaging data, including CT and MRI images, to predict tumor growth, distinguish between benign and malignant tumors, and even help with treatment planning. Brain tumors pose significant problems since they can differ in size, location, and shape within the brain. Radiologists have to carefully review the massive amounts of imaging data provided by traditional detection methods, such as MRI and CT scans. Nevertheless, this procedure can be lengthy and susceptible to human mistakes, potentially hindering timely treatment choices. Conversely, deep learning employs artificial neural networks to autonomously recognize and extract complex patterns from medical imaging. This technology has made it possible for computers to rapidly and precisely interpret MRI and CT scans, assisting radiologists in identifying even the smallest anomalies that might indicate the existence of a brain tumor.

Brain tumor prediction and treatment are greatly improved when genetic information and patient history are incorporated into DL models. A more thorough understanding of tumor features and patient outcomes is made possible by this multimodal approach. Genetic information sheds light on the

chemical and genetic changes linked to brain cancers. DL algorithms can find patterns associated with tumor behaviour, aggressiveness, and responsiveness to treatment by examining particular genetic markers and mutations. The combination of genetic data and patient history with imaging data, such as MRI scans, represents a multimodal approach to brain tumor prediction. This integration allows DL models to analyse diverse data types simultaneously, enhancing their ability to detect tumors, classify subtypes, and predict patient outcomes. Such comprehensive models can lead to better-informed clinical decisions, ultimately improving patient care and treatment efficacy.

There are some challenges for brain tumor prediction using DL such as limited dataset and imbalanced data. There are frequently few high-quality, annotated datasets available for DL model training. The variety of tumor forms and patient demographics may not be adequately represented in many of the datasets that are currently available. Tumor characteristics may be obscured by noise and abnormalities in medical pictures. These noises may be difficult for DL models to distinguish from real tumor features.

The primary goal of this paper is to conduct an in-depth review of research studies focused on brain tumor detection employing deep learning techniques. The opening section presents the introduction. The subsequent section discusses the application of deep learning models for identifying brain tumors.

2. Objectives

To study and analyze the various techniques for the Brain Tumor disease prediction using neural network. Data preprocessing of selected dataset. (Normalization and gray scaling). Comparative Analysis of the existing system to assess effectiveness and efficiency of proposed model. Use classification techniques using deep learning algorithm and develop a model. Performance analysis using evaluation metric.

3. Methods

In the realm of medical imaging, deep learning has emerged as a powerful instrument, particularly for detecting and classifying brain cancers. DL models have demonstrated greater accuracy in diagnosing brain tumors through MRI scans. Various types of brain tumors, including gliomas, meningiomas, and pituitary tumors, can also be diagnosed using deep learning models. In the first phase of model building we collect the dataset from different sources. This dataset include MRI scan images from different radiologist. After that we pre-process the dataset such as resize the images, rotate the images and convert the images into grayscale image. We should remove the noise from the images to extract the features. We use high pass filtering, low pass filtering, Gaussian filters to remove the noise from the images. Different types of features we can extract from the dataset such as shape based features, intensity based features and model based features. In the next phase we perform classification of the images using CNN, ANN, autoencoder models. In this phase we can classify the images into healthy image and tumour image.

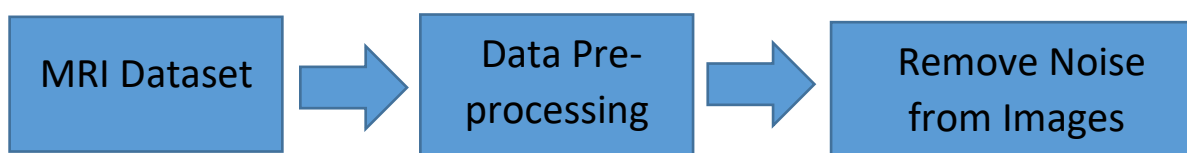




Figure 01: Flow of DL model building

4. Literature Survey

A research paper by Arvanitis et al. highlighted the intricate interactions within brain tumors and underscored the significance of the blood-brain and blood-tumor barriers regarding brain tumors and metastasis. Deeksha et al. employed CNN to classify brain tumors and their various types, showcasing the promising use of deep learning in the precise classification of brain cancers [1]. Nazir et al. conducted a comprehensive analysis of deep learning's application in brain tumor detection and classification between 2015 and 2020, highlighting the significant advancements in this field [1]. Amin et al. also contributed to the literature by surveying machine learning algorithms for brain tumor classification and detection, providing insights into the many methods employed in this field [1].

The application of transfer learning, a machine learning technique that repurposes models trained for one task to address related issues, has significantly improved medical picture analysis. By refining current models such as ResNet152, VGG19, DenseNet169, and MobileNetv3, researchers can achieve remarkable precision levels and optimize performance in applications such as brain tumor classification [2]. According to Praveen Kumar Ramtekkar, Anjana Pandey, and others, the technique identifies cerebral neoplasms from MRI scans with an astounding 98.9% accuracy rate. This high level of accuracy is a major advancement in the early detection of brain tumors, which can have a substantial impact on treatment outcomes [3]. Following picture segmentation, the GLCM (Grey Level Co-occurrence Matrix) is used in this research to extract features. The study of Soheila Saeedi, Sorayya Rezayi, and others on MRI-based brain tumor identification using convolutional DL methods and machine learning techniques presents several practical implications for the medical business, particularly in radiology and oncology. The study achieved high training accuracies of 95.63% for the auto-encoder network and 96.47% for the proposed 2D CNN. This level of accuracy can significantly improve the diagnosis of brain tumors, allowing for earlier and more accurate tumor detection, which is essential for effective treatment [4].

Novsheena Rasool, Javaid Iqbal Bhat uses MRI images from the various sources. They study and apply machine learning and DL algorithms on MRI dataset. They were gradually investigating other CNN-based architectures, such as encoder-decoder, cascaded, ensemble, and hybrid models, to address the complicated issues related to brain malignancies [5]. K. Bhagyalaxmi, B. Dwarakanath, and others analyze existing techniques, such as feature extraction with and without optimization procedures. Furthermore reviewed were the classification of brain cancers utilizing correntropy-based joint learning, deep transfer learning with Google-LeNet, mask-RCNN with DenseNet-41, ensemble learning, extreme machine learning, hybrid CNN features with SVM, and other DL approaches currently in use [6]. Praveen Kumar Ramtekkar, Anjana Pandey, and others preprocess the MRI scans

using a composite filter that comprises mean, median, and Gaussian filters. Images are segmented using threshold and histogram techniques. The GLCM is used to extract features. To select the best features, the optimized convolution neural network (CNN) approach employs whale optimization and grey wolf optimization. Brain cancer is detected using the CNN classifier. The accuracy of this improved approach in identifying brain tumors has been evaluated at 98.9% [7]. Studies on the classification of three and four distinct types of patients with brain tumors are conducted by Sohaib Asif, Ming Zhao, and others; all images were enhanced during the pre-processing stage using image processing techniques. To enhance classification performance, our deep dense block and softmax layer were added to the previous designs. On the 3-class and 4-class datasets, the suggested model's overall classification accuracy is 99.67% and 95.87%, respectively [8]. CNN and other DL models are used by Mohammed H. and others to obtain precise results. The model performs better overall as the dataset size is increased since it increases accuracy and generalizes the model. Higher accuracy is achieved by increasing the number of training epochs. Along with high values in other metrics, a high accuracy was achieved by using 60 epochs. The results of the experiment showed that 4976 samples were used to reach an accuracy of 97.4% [9]. Kamini Lamba, Shalli Rani, and colleagues create an automated method to detect brain tumors using publicly accessible brain MRI datasets. The suggested technique increases the image sizes while preserving uniformity by using data augmentation. After transfer learning, they employ a 16-layer visual geometry group to reduce the amount of work needed by medical professionals to obtain precise results. They use supervised learning and linear support vector machines (SVM) to extract the most important information and increase the speed and accuracy of diagnosis. With 98.87% accuracy, 99.09% precision, 98.73% recall, 99.02% specificity, and 98.91% F1-score, the suggested model performs better than the competition [10].

BrainNet is introduced by Tripty Singh, Rekha R. Nair, and others. The CNN architecture was created to classify brain tumors into different groups. Outstanding results were obtained in the classification of brain cancers using the BrainNet CNN architecture. Its testing accuracy was 97.71% and its training accuracy was an impressive 99.96%. The usefulness of the suggested architecture in this field is demonstrated by the fact that this performance is noticeably better than that of well-known pre-trained models. Five popular pre-trained architectures—VGG19, VGG16, VGG13, ResNetV2, and Inception—were used to compare BrainNet. The outcomes demonstrated that BrainNet performed better than these models, confirming its architecture and efficacy in tasks involving the categorization of brain tumors [14]. Using MRI data, T. Lakshmi Prasanthi and N. Neelima report a number of important findings about how well various DLmodels perform in the classification of brain cancers. A precision of 96.63% was attained using the novel CNN method created in the study. This suggests that brain cancers can be diagnosed with great accuracy. Glioma tumor detection was a strong suit for VGG19 and InceptionResNetV2. Other models, such as DenseNet121 and EfficientNet B7, also shown encouraging precision rates, which made them suitable choices for the classification of brain tumors [15].

Monika Sachdeva, Chandni, and others In contrast to conventional techniques, the study suggests a fully automated DLmodel created especially for the diagnosis of brain tumors, which improves tumor detection efficiency and accuracy. The suggested model effectively extracts features and classifies medical images by combining the benefits of residual connections and inception modules. Using two

publicly available datasets with 4600 and 253 brain pictures, the experimental evaluations show that the suggested architecture achieves an overall classification accuracy of above 99%. This performance shows a significant advance in diagnostic capabilities, surpassing that of earlier investigations [17]. Amita Nandal, Shyo Prakash Jakhar, and others This research proposes a novel network topology called the Multi-scale Fractal Feature Network (MFFN), which increases the sensitivity and accuracy of brain tumor segmentation. This method makes advantage of multi-scale pixel segmentation and classification, which is well known for its precision and potency in tumor detection. Using the ideas of fractal geometry, the authors construct a fractal residual structure inside the MFFN. This new technique improves the network's performance by utilizing the unique properties of fractals, which can spot complex patterns in the data [18].

Kavita A. Sultanpure, Jayashri Bagade, and others Input photos are extracted from cloud storage for analysis. The PSO algorithm selects features to categorize brain tumors. Images of brain tumors were correctly classified using CNN and SVM. SVM maximizes data margins between datasets. Using machine and DL approaches, Md. Shafiul Azam, Md. Naim Islam, and others are working to develop an enhanced system for the detection and categorization of brain tumors (BT). DL techniques were used, such as the CNN Long Short-Term Memory (LSTM) model, the CNN 2D CNN with 13 layers, and another CNN with 9 levels. Impressive accuracy rates were attained by the models. 98.47% for 2D CNN LSTM, 97.71% for 2D CNN (9 layers), and 92.36% for 2D CNN (13 layers). These DL methods were combined to create the ensemble model. They receive precision of 99% and overall accuracy of 98.82%. presented a new ensemble model that adds fully connected layers to the CNN and CNN LSTM models, improving the default architecture. showed how important ensemble learning is for enhancing the classification performance of medical images [20]. Venkatesh Pulletikurthi, Rita Appiah, and others first used CNN in conjunction with Proper Orthogonal Decomposition (POD) to detect brain tumors. The goal of this integration is to improve tumor detection's accuracy and dependability, particularly when using sparse MRI scan data. achieved a remarkable 99.21% tumor identification accuracy using CNN [21].

5. Discussion – A Comparative Analysis

A comparative study of the literature review conducted by several writers is presented in this section. The detailed analysis and methods the researchers used to train the models are shown in the following table.

Table 5.1 Comparative Analysis

Authors and their work	Methodology and Dataset Used	Analysis	Limitations
Praveen Kumar Ramtekkar, Anjana Pandey, and others Utilized MRI imaging for tumor analysis [3].	Use GLCM for texture-based feature extraction.	Achieved 98.9% precision in identifying cerebral neoplasms from MRI scans. Facilitates early detection, significantly improving therapeutic outcomes	GLCM is sensitive to noise reduction. These can be affect to feature extraction.

<p>Soheila Saeedi, Sorayya Rezayi and others Utilized MRI imaging as the primary data source [4].</p>	<p>Implemented 2D CNN and Auto-encoder network.</p>	<p>The accuracy of the auto-encoder network was 95.63%, whereas that of the suggested 2D CNN was 96.47%.</p>	<p>Use a small dataset only. The model must be trained using a variety of datasets.</p>
<p>Novsheena Rasool, Javaid Iqbal Bhat Utilized MRI images from diverse sources for analysis [5].</p>	<p>Use Encoder-Decoder Models For image segmentation and feature extraction. Cascaded Models use for Layered approaches to refine predictions step-by-step. Combining multiple models for improved robustness and accuracy using Ensemble model</p>	<p>Focused on addressing the complex challenges in brain tumor detection.</p>	<p>The encoder-decoder requires a lot of processing power. Cascaded models are quite complicated and take longer to train.</p>
<p>K. Bhagyalaxmi and others perform Comprehensive review of existing techniques for brain tumor detection and classification [6].</p>	<p>Perform Hybrid CNN Features with SVM for Combining DL features with classical machine learning for robust classification</p>	<p>Uses advance model like Google-LeNet Encodings via Transfer Learning, Mask-RCNN with DenseNet-41.</p>	<p>The pipeline becomes more complex when DL and traditional machine learning are combined, necessitating extra processes for feature extraction, pre-processing, and integration.</p>
<p>Praveen Kumar and others Focus on developing an optimized CNN-based system for brain tumor detection [7]</p>	<p>MRI images preprocessed using Gaussian filter, Mean filter and Median filter. Applied thresholding and histogram techniques for effective image segmentation</p>	<p>Achieved accuracy of 98.9%. Of optimizes CNN. Uses WOA and GWO for optimization.</p>	<p>Gaussian filtering works well to reduce noise, but it might obscure small details in images, which could be important for medical research.</p>
<p>Sohaib Asif and others Focused on categorizing brain tumors into three and</p>	<p>To improve feature extraction, a Deep Dense Block was added to the base</p>	<p>Accuracy of 99.67% for three-class classification and 95.87% for four-</p>	<p>Performance and efficiency may suffer if redundant or unnecessary features are</p>

four different classes [8].	designs. A Softmax layer was added for efficient multi-class categorization.	class classification were attained.	introduced by combining the outputs from all earlier stages.
Mohammed H. Al-Jammas and others utilized a dataset of 4,976 samples for robust training and evaluation [9]	Focused on achieving accurate results in brain tumor detection using CNN.	Achieved a high accuracy of 97.4%.	Use a small dataset. The model must be trained using a variety of datasets.
Kamini Lamba and others Focused on developing an automated system for diagnosing brain malignancies using publicly available MRI datasets [10].	To increase image size and preserve consistency throughout the collection, data augmentation was used. used a 16-layer Visual Geometry Group (VGG-16) architecture for transfer learning.	98.87% accuracy was attained. Recall receives 98.73% and precision receives 99.09% accuracy.	Improper augmentation methods might generate biases or artifacts that are absent from real-world data.
Shenbagarajan Anantharajan and others Developed a system to classify normal and abnormal brain tissues from MRI images [11].	Preprocessed MRI images were segmented using fuzzy C-Means (FCM). Proposed the classifier EDN-SVM.	Achieved accuracy of 97.93%. Extracted features using GLCM,	FCM is highly sensitive to noise such as motion blur and intensity inhomogeneity
Monika Agarwal and others tested on the openly accessible FigShare database for validation [12].	Low-contrast MRI images were improved using ODTWCHE used the pre-trained model from Inception V3 to automatically extract both low-level and high-level features.	Efficiently handles low-contrast MRI images, improving diagnostic accuracy and reliability.	ODTWCHE doesn't specifically address noise reduction, it performs less well on images with a lot of noise.

<p>Tripty Singh and others Proposed BrainNet, a CNN architecture tailored for classifying brain tumors into distinct categories [14]</p>	<p>A custom CNN architecture designed specifically for brain tumor classification into distinct categories.</p>	<p>Achieved 99.96% training accuracy and 97.71% testing accuracy</p>	<p>Make use of a limited dataset. A range of datasets must be used to train the model.</p>
<p>Among others, T. Lakshmi Prasanthi Concentrate on assessing how well various DLmodels perform in identifying brain cancers using MRI data. [15].</p>	<p>Comparing precision rates across CNN, VGG19, InceptionResNetV2, DenseNet121, and Efficient Net B7.</p>	<p>The innovative CNN-based model developed in the study achieved 96.63% precision, indicating a high level of accuracy in diagnosing brain tumors.</p>	<p>The model's accuracy has to be increased.</p>
<p>Two public datasets of 4600 and 253 brain pictures were used for testing by Chandni, Monika Sachdeva, and others [17].</p>	<p>The suggested approach incorporates the advantages of residual connections and inception modules, which enable efficient feature extraction and categorization of medical images.</p>	<p>Obtaining a classification accuracy of more than 99% overall.</p>	<p>It requires highly computational powers and difficult to integrate with images.</p>
<p>Sultanpure, Kavita A., and others centered on comparing various machine learning models for classifying brain tumors and using cloud storage for image processing [19].</p>	<p>PSO algorithm was employed for feature selection.</p>	<p>Employs Extreme Learning Machines (ELM), SVM, and CNNs for classification. CNNs were more accurate at detecting brain cancers.</p>	<p>PSO is sensitive to hyper parameters and it is difficult to handle large dataset.</p>
<p>Islam, Md. Naim, and others centered on sophisticated machine learning and deep learning methods for brain tumor detection and classification [20].</p>	<p>To enhance performance, fully connected layers were added to the CNN and CNN-LSTM models.</p>	<p>The ensemble model achieved Overall Accuracy 98.82% and Precision: 99%.</p>	<p>This model is difficult in the optimization and reduces interpretability.</p>

<p>Rita Appiah as well as other originally presented the use of POD and CNN together to detect brain tumors [21].</p>	<p>POD-CNN model was designed to improve the reliability and accuracy of tumor detection, especially with minimal MRI scan data. Conducted a comparative analysis of MobileNetV2, Inception-v3, ResNet101 and VGG-19.</p>	<p>MobileNetV2 was identified as the best-performing model, achieving 99.21% accuracy in tumor detection.</p>	<p>it have requires high raining time for optimize model performance.</p>
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6. Conclusion

DL has emerged as a powerful model, particularly for the detection and classification of brain tumors. In this paper we discuss about detail comparative analysis of DL model used for brain tumors detection. CNN, ResNet152, VGG19, DenseNet169, and MobileNetv3, VGG-19, SVM, CNN LSTM models applied successfully for detection of brain tumors at early stage. The absence of high-quality datasets, model interpretation, and variances in model performance are some of the difficulties for brain tumors detection. DL models have a potential to overcome all the challenges and helps healthcare professionals for higher accuracy.

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