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Article Title: A Comprehensive Review of Brain Tumor Detection Using Deep Learning and Machine Learning Classifiers

A Comprehensive Review of Brain Tumor Detection Using Deep Learning and Machine Learning Classifiers

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ABSTRACT

A brain tumor is a destructive or non destructive anomalous tissue in the brain which affects the lifestyle of peoples. It affects the survival rate of the patients and even causes death. The conventional techniques for brain tumor detection is highly challenging and time consuming procedure. For the purpose of early brain tumor diagnosis, Brain Tumor Categorization (BTC) from Magnetic Resonance Imaging (MRI) images is extremely crucial. This paper provides a comprehensive review of brain tumor analysis using a Deep Learning (DL) and Machine Learning (ML) methods from MRI images. These models considerably upgrade the automated brain tumor diagnosis, and help the physicians and specialists to proficiently identify the tumor affected area. In this study, the DL techniques and the ML techniques are evaluated for the purpose of brain tumor identification using MRI scans. It significantly enhances the precision of medical assessments and treatment procedures and assists in separating healthy cells and tumor affected cells.

Keywords: Brain tumor detection, Deep learning (DL), Machine learning (ML), Magnetic Resonance Imaging (MRI), Brain Tumor Categorization (BTC).

1 Introduction

The brain is a complicated part of the body that controls entire neural system, and it is responsible for memory, vision, breathing, emotion, skills, and every process that controls the body. A brain tumor is a destructive disorder that is triggered by the intensive growth of anomalous cells in the brain. The brain tumors are considered to be two forms such as malignant (cancerous) and benign (non cancerous). The anxiety in the cranium increases the development of malignant and benign tumors, and this provokes neurotrauma and indeed death. The brain tumors, which is located inside the brain cell is called gliomas and the tumors that spread towards the blood circulation is called brain metastases. A malignant brain tumor is highly infectious in the brain cell and leads to death. Severe head pain, amnesia, inattention, muscle weakness, unsteadiness, and coordination impairment are the major indications of a brain tumor [1].

In the initial stage, the tumor size is very small, so it is very hard to analyse. There are various medical devices like Computer Tomography (CT) scans, Simple Photon Emission Computer

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Tomography (SPECT), MRI scans, ultrasound, Position Emission Tomography (PET), and X-rays are used for the brain tumor diagnosis. From these techniques, MRI is considered to be the best diagnostic system because it offers high-resolution images of brain cells. It is employed to determine the size and physical position of the brain tumor. MRI act as a non-aggressive molecular marker of organic gene expression and enables the relationship between imaging diagnostics and molecular [2].

The Brain Tumor Segmentation (BraTS) dataset contains multifaceted MRI images, which is necessary for brain tumor classification, division, and detection. It offer high-grade, unidentified, and systemized data for many applications machine learning and deep learning techniques. This datasets adapts numerous MRI techniques including T1-weighted images, T1Gd (T1 post-contrast gadolinium-enhanced), T2-weighted images, Fluid Attenuated Inversion Recovery (FLAIR) for the comprehensive analysis of brain tumor. T1 denotes longitudinal relaxation time of the brain tissues and it offers complete anatomical position of the brain. T2 denotes transverse relaxation time of the brain tissues and it emphasize the relation between abnormal and normal brain tissues. FLAIR is utilized to define the precision of brain tumor analysis and also used to predict the patient's survival rate [3].

In early period, various conventional techniques are used to classify the brain tumor. This approaches identifies the high-grade malignant tumors with improved categorization accuracy. However, the conventional techniques take more time for categorization process. It has poor data quality and it is difficult to selecting a desirable parameter for clustering. Further, this technique need some significant resources, so that this approach has challenges on the real-time clinical setting. In order to overcome the limitations in the conventional techniques, Computer-Aided Diagnosis (CAD) system is used for automatic diagnosis of brain tumor.

Nowadays, many researchers have progressed various techniques like reinforcement, supervised and unsupervised ML techniques, DL techniques, transfer learning techniques and Artificial Intelligence (AI) for the early diagnosis of this disease. Among these techniques, Convolutional Neural Network (CNN) is extensively utilized in the CAD system. The CNN is used to execute many applications like medical imaging, classification and surveillance. Initially, the CNN network contains three layers such as convolutional layer, pooling layer, and Fully Connected (FC) layer. Convolutional layer is used to extract the features of the input images by employing various filters. Pooling layer is also known as downsample layer, and it is manipulated for reducing the spatial dimensions and also reduce the parameters of the input images. FC layer is used to execute the classification process by extract the features from convolutional layer and pooling layer [4].

However, predicting survival rate of the patient is very difficult, so need to develop various treatments for ensure the patient's outcome. In recent times, several ML algorithms are developed, and which employs training and testing dataset to prognosticate survival rate of the

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patient. The irregular informations in the datasets are resolved by using Synthetic Minority Oversampling Technique (SMOTE) and Adaptive Synthetic (ADASYN) method which improve the prediction outcome and classification process of ML algorithms. It employs several regression method such as, Linear Regression (LR), Ridge Regression (RR), Extreme Gradient Boost (XGBoost) for survival rate prediction on the basis of input characteristics. LR is the commonly used regression algorithm, which presume a linear relation between input characteristics and experimental variables, and it reduces the variation of expected value. RR is employed to reduce the variation and overfitting in the model [5].

This study provides a comprehensive review of brain tumor detection using ML and DL classifiers from MRI images. By evaluating these approaches and estimating their benefits and limitations, the performance and precision of the system is increased.

The most significant goal of this review is to identify the brain tumor by employing ML techniques and DL techniques. The optimization of these approaches are intensively discussed below.

1. To analyse the brain tumor by using ML techniques.
2. To analyse the brain tumor by using DL techniques.
3. To predict brain tumor survival rate of the patients.
4. To enhance the precision and performance of these techniques.

2 Review of Comprehensive Analysis of Brain Tumor by Using Machine Learning Methods

2.1 Semi-Supervised Brain Tumor Classification Network (SSBTCNet)

The author of [6] describes a Semi-Supervised Brain Tumor Classification Network (SSBTCNet) architecture which incorporates an unsupervised Auto Encoder (AE) and supervised Classification Networks (CN) for the categorization of glioma, pituitary, meningioma and no tumor images. The MRI images are provided to the SSBTCNet to perform classification process. BD1-without augmentation dataset and BD2-with augmentation dataset are used to validate the efficiency of this architecture. The SSBTCNet model comprises AE network and CN network based on input data. The AE network is employed to decrease the Reconstruction (RE) between the input and output of the image, and the CN network is employs concealed descriptor to reduce cross entropy loss (L_C). A fuzzy-logic based method is used to train and test the datasets in order to enhance the efficiency of SSBTCNet architecture. This method effectively classifies the brain tumor-affected area and the non-affected area in less time and makes the model more robust. However, this approach is not able to verify the huge data set, and it increases the data fluctuation when decreasing overfitting. Moreover, this method can’t able to disclose the position of the brain tumor and also not applicable for 3D informations.

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2.2 K-Nearest Neighbour (KNN), Multi-Class Support Vector Machine (MSVM) And Neural Network (NN) Classifiers

This study presented a K-Nearest Neighbour (KNN), multi-class Support Vector Machine (m-SVM), and Neural Network (NN) classifiers based on ML algorithm to categorize the high-grade malignant brain tumors like metastasis, central intraventricular neurocytoma, intraventricular malignant mass, astrocytoma, and gliomas. KNN is a linear classifier which is used to evaluate the classification result. Initially, the value of k is taken as 2, then frequently increase the k value until the classification accuracy rate is increased. Generally, the nearest neighbour value is not less than the number of discrete labels available in the training datasets. The range of k value is mentioned as $0 < k \leq n$; here, n is represented as total number classes in the dataset. The m-SVM is a non-linear classifier that is used to solve the pattern categorization problem along with binary distinction. SVM consist of two approaches like, one-against-all classification and ranking based multi class classification to perform multi-class classification. In this study, one-against-all classification is employed to identify and categorize the correct brain tumor images. The NN is a probabilistic classifier, which have the ability to predict the probability values that determines class labels. It comprises various components such as, input (Xi), activation function $(\emptyset)$, initial weight (Wi), and output (Yi). The NN architecture contains three layer, the input layer have data values, the hidden layer have initial weights, and the output layer denotes class labels. The NN classifier uses varied features to provide high accuracy rate. However, this model have poor scalability and only suitable for small datasets [7].

2.3 Hybridized Support Vector Based Random Forest Classifier (HSVFC)

This study presented a hybridized ML technique based on Maximum a Priori (MAP) firefly algorithm which incorporates Random Forest (RF) method and Support Vector Machine (SVM) for detecting brain tumor and stroke from MRI scans. The Hybridized Support Vector based random Forest Classifier (HSVFC) is developed based on binary labelling to effectively classifies the low grade brain tumor, high grade brain tumor, sub-acute stroke and acute stroke. The following equation represents the weight vector (W_K) calculation by using Lagrange multipliers.

$$W_K(t_f) = \lim_{k \to 1\ to\ CL} \lim_{t_f \to 1\ to\ FD} \sum_{0=1}^{I_{Tr}} \alpha(0) * L(0) * Train_{fes}[0, t_f] \quad (1)$$

Where CL denotes the total number of class, FD represents the extracted features, I_{Tr} indicates the stroke images, α is the Lagrange multiplier vector, and $Train_{fes}$ is the input dataset. Then, CL is divided into two classes by using bias vector (B_K) is given below,

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$$B_K(t_f) = \frac{1}{I_{Tr}} \lim_{k \to 1\ to\ CL} \lim_{t_f \to 1\ to\ FD} * \sum_{0=1}^{T_r} \left(L(0) - Train_{fea}[0, t_f] * W_k(t_f) \right) \quad (2)$$

The Support Vector (SV) is established to find the margins between two classes.

$$SV_K(t_f) = \lim_{t_f \to 1\ to\ FD} \left(\frac{-B_K(t_f)}{W_K(t_f)}\right) \quad (3)$$

The hyper parameter contains least number of observation per leaf (minleafsize) and Out-Of-Bag error Prediction (OOBPred), which is used to train and test the features of RF classifiers. Then, the decision tree is measured as,

$$\hat{f}_k(u) = \lim_{k \to 1\ to\ CL} \lim_{u \to 1\ to\ I_{Te}} \lim_{t_f \to 1\ to\ FD} \{ f_k(Test_{fea}[u, t_f]) \} \quad (4)$$

Here f_k represents the decision tree. The following equation represents the classified brain tumor types.

$$class\ (u) = \lim_{u \to 1\ to\ I_{Te}} \left(\arg \max_{k \to 1\ to\ CL} \left(\hat{f}_k(u) \right) \right) \quad (5)$$

And also several affected regions like tumor necrosis, edema, and tumor necrotic are identified and emphasized by various colours. However, this model susceptible to overfitting and it have high convergence rate. It is not applicable to handle large database [8].

3 Review of Comprehensive Analysis of Brain Tumor by Using Deep Learning Methods

3.1 Convolutional Neural Network (CNN)

This study demonstrated a novel, a CNN model for the categorizing the two types of brain tumors like Low-Grade Glioma (LGG) and High-Grade Glioma (HGG) from multifaceted MRI images. The BraTS datasets combines MRI images of the patients having LGG and HGG brain tumors. The BraTS dataset utilizes in the CNN network to perform classification process and it contains TI, T2, and FLAIR images. Sigmoid function is employed in the Fully Connected (FC) layer to find a binary classification result, which is given below;

$$Sigmoid\ (x) = \frac{1}{1+e^{-x}} \quad (6)$$

Where, x represents the output of the FC layer in CNN. Then, Dice Similarity (DS) metric is utilized to validate the classification process. This model increases the performance and reduces the complexity of the algorithm. However, this network causes overfitting and not suitable for real time applications in clinics [9].

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3.2 UNet and ResUNet+ Architectures

This study presented a convolutional based ResUNet+ model which is influenced by UNet architecture for brain tumor segmentation. The main goal of using UNet architecture is to extract global and local features at different scales. By using skip connections, it carry the extracted features from encoder to decoder. For the purpose of enhancing the architecture's performance, the convolution is applied in the Region of Interest (ROI). Then, the UNet and ResUNet+ models are trained and validated by using BraTS datasets which comprises information about pilocytic astrocytoma and glioblastoma multiforme. The BraTS dataset contains T1 module, which classifies the normal cells, T2 module classifies the inflated tumor region, and FLAIR module differentiate the tumor region from the cerebrospinal fluid. This model efficiently detect the brain tumor and enhance the performance. The computational cost is reduced. However, this method utilizes limited modalities and takes more time to train the datasets [10].

3.3 Multi Scale Convolutional Neural Network (MSCNN)

The work [11] proposes a Multi- Scale Convolutional Neural Network (MSCNN) technique for brain tumor categorization by using MRI scans. The input layer of MSCNN network contains 10×10 scale, 20×20 scale and 34×34 scale, which are down-sampled to extract the features by various channels. The Three-Dimensional (3D) information from MRI images employs T1- weighted, T2- weighted and PD- weighted pulse sequence and these images are categorized into primary input image, contour image data, and gold standard image data for accurately classify the brain tumor. To enhance the accuracy, the MSCNN sent the information through slice sequences. This MSCNN model reduces the calculation time and efficiently encapsulate the multi-scale information. However, the proposed technique require some data resources, and it is insufficient for large-scale clinical applications.

4 Comparative Analysis

A comparative analysis of brain tumor detection using various ML and DL classifiers are discussed below in Table 1 and Table 2.

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Table 1: Comparable analysis of brain tumor detection using ML techniques.

SI. No.	Author/ Year of publication	Methodology	Advantages	Limitations
1.	Bhargav Mallampati *et al* (2023)	This study proposed a hybrid ML model based on 3D-UNet and 2D-UNet to categorize the brain tumor.	This model takes less time to classify the brain tumor from MRI scans.	The sample size of the available features are not enough to train the model and it is not suitable to handle large datasets.
2.	Jyotismita Chaki *et al* (2023)	This paper presented a Deep Brain Incep Res Architecture 2.0 Reinforcement Learning Network (DBIRA2.0-RLN) for brain tumor classification.	This technique reduces overfitting and make the model more robust.	This method consumes more time and not suitable to validate large dataset as well as 3D informations.

Table 2: Comparative analysis of brain tumor detection using DL techniques.

SI. No.	Author/ Year of publication	Methodology	Advantages	Limitations
1.	Neelum Noreen *et al* (2020)	A DensNet201 and Inception-v3 models are developed for the identification of brain tumor by using MRI.	This model achieves better performance and high precision regarding brain tumor.	However, this network require large number of datasets to train the model.
2.	Hasnain Ali Shah *et al* (2022)	A well-defined Convolutional Neural Network (CNN) EfficientNet-B0 architecture is developed for brain tumor categorization.	This model attains efficient performance and precision in the identification of brain tumor and upgrades the quality of MRI images.	However, this approach is time consuming and not applicable for clinical images such as radiography, Computer Tomography (CT), and x-ray.

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Table 3: Comparative analysis of accuracy in ML techniques.

Methods	Accuracy
HSVFC [8]	88.3%
3D-UNet [12]	71%
DBIRA2.0-RLN [13]	97.5%

Table 3 represents an accuracy comparison of brain tumor analysis using ML techniques. From the table, it is verified that the DBIRA2.0-RLN [13] model achieves higher accuracy of 97.5% when compared with HSVFC [8] model and 3D-UNet [12] model.

Table 4: Comparative analysis of accuracy in DL techniques.

Methods	Accuracy
CNN [9]	99.85%
Inception-v3 and DensNet201 [14]	99.51%
EfficientNet-B0 [15]	98.87%

Table 4 represents an accuracy comparison of brain tumor analysis using DL techniques. The table confirms that the CNN [9] method exceeds the Inception-v3, DensNet201 [14], and EfficientNet-B0 [15] models in terms of accuracy with 99.85%.

5 Conclusion

The early identification and categorization of brain tumor by manipulating advanced techniques are become more important in today’s society. Researchers have established various approaches to enrich the categorization accuracy of brain tumor. The approaches utilizes hybrid algorithms and more number of training datasets to obtain more accurate classification results. In this research, several ML and DL techniques are reviewed for the brain tumor detection from MRI images with high accuracy and performance. Initially, five ML models such as, SSBTCNet, KNN, m-SVM, and NN classifier, HSVFC, 3D-UNet, and DBIRA2.0-RLN are compared for the analysis of brain tumor. Likewise, five DL techniques such as, CNN, UNet & ResUNet+, MSCNN, DensNet201 and Inception-v3, and EfficientNet-B0 are compared for the brain tumor analysis. It is verified that, the CNN method based on DL model results better performance and higher precision rate when compared to several ML techniques. Furthermore, the future study is prolonged towards the use of advanced optimization algorithms for the multiclass classification.

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