International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 01 | January - 2024 SJIF Rating: 8.176 ISSN: 2582-3930

A Survey on Brain Tumor Classification Using Machine Learning Techniques

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Abstract: **Machine learning (ML) models have emerged as powerful tools in the field of medical diagnostics, particularly in the classification of brain tumors. These models leverage advanced algorithms to analyze complex patterns within medical imaging data, providing valuable insights for accurate and timely diagnosis. The application of ML in brain tumor classification holds immense promise for improving patient outcomes through early detection and tailored treatment plans. The success of machine learning models in brain tumor classification heavily relies on the quality and quantity of the data used for training. Medical imaging data, such as MRI scans, are commonly employed. Pre-processing steps, including normalization and augmentation, are crucial to enhance the robustness of models and ensure accurate classification. Additionally, the availability of well-curated and diverse datasets is essential for training models capable of handling variations in tumor characteristics. This paper presents a comprehensive survey on machine learning and deep learning models for brain tumor classification.**

***Keywords*—Brain Tumor Classification, Feature Extraction, machine learning, automated classification, classification accuracy.**

1. Introduction

Machine learning models for brain tumor classification often involve the extraction and selection of relevant features from medical images. Techniques like convolutional neural networks (CNNs) excel in automatically learning hierarchical representations directly from raw image data. These features capture intricate details, aiding in the discrimination of tumor types based on shape, texture, and spatial relationships within the brain.

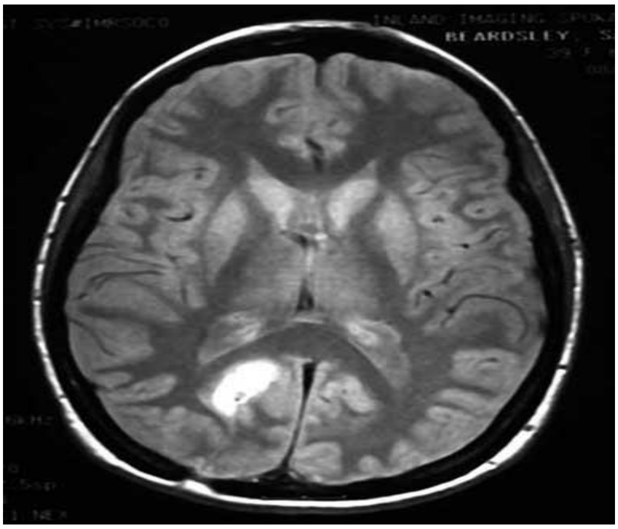

Fig. 1 A typical brain MRI scan image

Since various machine learning architectures are employed for brain tumor classification, with CNNs being particularly prevalent. These architectures enable the automatic extraction of hierarchical features from medical images, facilitating the model's ability to discern subtle patterns indicative of different tumor classes. Transfer learning, where pre-trained models on large datasets are fine-tuned for specific tasks, has proven effective in scenarios with limited labeled medical data. The training process involves optimizing model parameters using labeled datasets, with a separate validation set to fine-tune hyperparameters and prevent overfitting. Rigorous validation is crucial to ensure the generalizability of the model to unseen data, enhancing its reliability in real-world clinical applications. Model performance metrics such as sensitivity, specificity, and area under the curve (AUC) are commonly used to evaluate the accuracy and efficacy of brain tumor classification models.

2. AUTOMATED DETECTION OF BRAIN TUMOURS

Machine learning models for brain tumor classification represent a transformative approach in medical diagnostics. The integration of advanced algorithms with medical imaging data offers the potential for more accurate and efficient diagnosis, paving the way for personalized treatment strategies. As research in this field continues to evolve, addressing challenges and refining model architectures will be essential for translating these innovations into impactful clinical applications.

Despite the progress, challenges persist in the development of machine learning models for brain tumor classification. The interpretability of complex models, ethical considerations in healthcare AI, and the need for large, diverse datasets are ongoing concerns. Additionally, model robustness across different imaging protocols and variations in tumor phenotypes must be addressed to enhance the reliability of these models in clinical settings

Based on the image processing and feature extraction, the classification is done. Automated classification requires training a classifier with the pre-defined and labelled data set and subsequently classifying the new data samples. Off late machine learning based classifiers are being used for the classification problems. Machine learning can be crudely understood as the design of automated computational systems which mimic the human behaviour and can be trained in the sense that they can learn from data fed to the system. Primarily machine learning is categorized into three major categories which are [13]-[15]:

1) Unsupervised Learning: In this approach, the data set is not labelled or categorized prior to training a model. This typically is the most crude form of training wherein the least amount of apriori information is available regarding the data sets.

2) Supervised Learning: In this approach, the data is labelled or categorized or clustered prior to the training process. This is typically possible in case the apriori information us available regarding the data set under consideration.

3) Semi-Supervised Learning: This approach is a combination of the above mentioned supervised and unsupervised approaches. The data is demarcated in two categories. In one category, some amount of the data is labelled or categorized. This is generally not the larger chunk of the data. In the other category, a larger chunk of data is un-labeled and hence the data is a mixture of both labelled and un-labeled data groups.

Some other allied categories of machine learning are:

4) Reinforcement Learning
5) Transfer Learning
6) Adversarial Learning
7) Self-Supervised learning etc.

While these learning algorithms can be studied separately, however they are essentially the modified versions of unsupervised, supervised and semi-supervised learning architectures. A more advanced and useful category of machine learning is deep learning which is the design of deep neural nets with multiple hidden layers.

Machine learning based classifiers are typically much more accurate and faster compared to the conventional classifiers. They render more robustness to the system as they are adaptive and can change their characteristics based on the updates in the dataset [16]. The common classifiers which have been used for the classification of pests are:

Regression Models: In this approach, the relationship between the independent and dependent variable is found utilizing the values of the independent and dependent variables. The most common type of regression model can be thought of as the linear regression model which is mathematically expressed as [15]:

$$\boldsymbol{y = \theta_1 + \theta_2 x} \quad \textbf{(1)}$$

Here,
x represents the state vector of input variables
y represents the state vector of output variable or variables.
Ө1 and Ө2 are the co-efficients which try to fit the regression learning models output vector to the input vector.
Often when the data vector has large number of features with complex dependencies, linear regression models fail to fit the input and output mapping. In such cases, non-linear regression models, often termed as polynomial regression is used. Mathematically, a non-linear or higher order polynomial regression models is described as:

$$\boldsymbol{y = \theta_0 + \theta_1 x^3 + \theta_2 x^2 + \theta_3 x} \quad \textbf{(2)}$$

Here,
x is the independent variable

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y is the dependent variable
$\theta_1, \theta_2 \ldots\ldots \theta_n$ are the co-efficients of the regression model.
Typically, as the number of features keep increasing, higher order regression models tend to fit the inputs and targets better. A typical example is depicted in figure 2

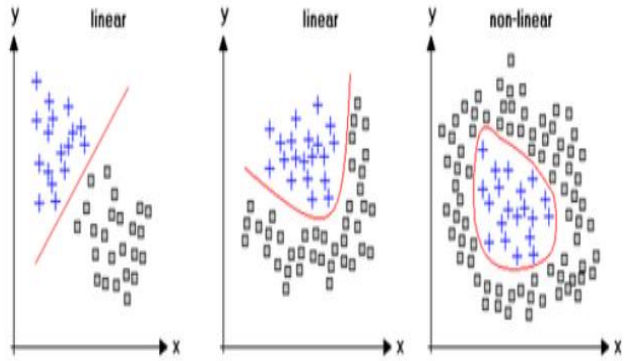

Fig. 2 Linear and Non-Linear Regression fitting [14]

Support Vector Machine (SVM): This technique works on the principle of the hyper-plane which tries to separate the data in terms of 'n' dimensions where the order of the hyperplane is (n-1). Mathematically, if the data points or the data vector **'X'** is m dimensional and there is a possibility to split the data into categories based on **'n'** features, then a hyperplane of the order **'n-1'** is employed as the separating plane. The name plane is a misnomer since planes corresponds to 2 dimensions only but in this case the hyper-plane can be of higher dimensions and is not necessarily a 2-dimensional plane. A typical illustration of the hyperplane used for SVM based classification is depicted in figure 3.

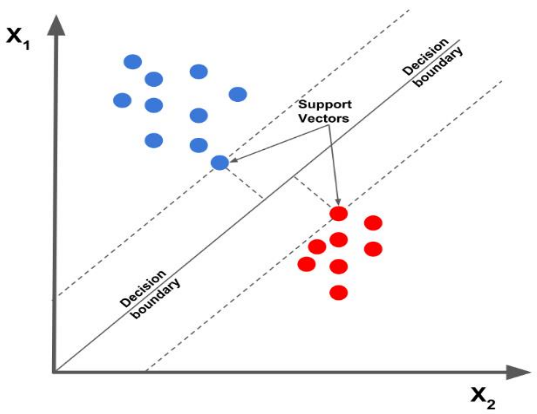

Fig. 3 Separation of data classes using SVM

The selection of the hyperplane H is done on the basis of the maximum value or separation in the Euclidean distance d given by:

$$\boldsymbol{d} = \sqrt{\boldsymbol{x_1^2} + \cdots \ldots \ldots \boldsymbol{x_n^2}} \tag{3}$$

Here,
x represents the separation of a sample space variables or features of the data vector,
n is the total number of such variables
d is the Euclidean distance

The (n-1) dimensional hyperplane classifies the data into categories based on the maximum separation. For a classification into one of **'m'** categories, the hyperplane lies at the maximum separation of the data vector **'X'.** The categorization of a new sample **'z'** is done based on the inequality:

$$\boldsymbol{d_x^z} = \boldsymbol{Min}(\boldsymbol{d_{C1}^z}, \boldsymbol{d_{C2}^z} \ldots \boldsymbol{d_{C2=m}^z}) \tag{4}$$

Here,
d_x^z is the minimum separation of a new data sample from **'m'** separate categories
$d_{C1}^z, d_{C2}^z \ldots d_{C2=m}^z$ are the Euclidean distances of the new data sample **'z'** from m separate data categories.

Neural Networks: Owing to the need of non-linearity in the separation of data classes, one of the most powerful classifiers which have become popular is the artificial neural network (ANN). The neural networks are capable to implement non-linear classification along with steep learning rates. The neural network tries to emulate the human brain's functioning based on the fact that it can process parallel data streams and can learn and adapt as the data changes. This is done through the updates in the weights and activation functions. The mathematical model of the neural network is depicted in figure 4.

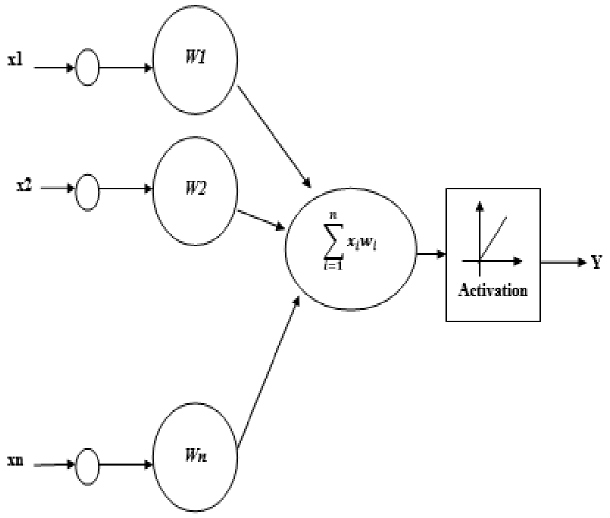

Fig. 4 Mathematical Model of Single Neuron [13]

The mathematical equivalent of an artificial neuron is depicted in figure 4 where the output can be given by:

$$\boldsymbol{y} = \boldsymbol{f}\left(\sum_{i=1}^{n} \boldsymbol{x_i w_i} + \boldsymbol{b}\right) \quad \textbf{(5)}$$

Here,
x denote the parallel inputs
y represents the output
w represents the bias
f represents the activation function

The neural network is a connection of such artificial neurons which are connected or stacked with each other as layers. The neural networks can be used for both regression and classification problems based on the type of data that is fed to them. Typically the neural networks have 3 major conceptual layers which are the input layer, hidden layer and output layer. The parallel inputs are fed to the input layer whose output is fed to the hidden layer. The hidden layer is responsible for analysing the data, and the output of the hidden layer goes to the output layer. The number of hidden layers depends on the nature of the dataset and problem under consideration. If the neural network has multiple hidden layers, then such a neural network is termed as a deep neural network. The training algorithm for such a deep neural network is often termed as deep learning which is a subset of machine learning. Typically, the multiple hidden layers are responsible for computation of different levels of features of the data. Several categories of neural networks such as convolutional neural networks (CNNs), Recurrent Neural Network (RNNs) etc. have been used as effective classifiers [17] .

III. Previous Work

This section cites the various contemporary approaches employed for automated pest and weed detection in plants. The salient features of each approach in terms of the technique adopted, performance metrics obtained and detected research gaps or limitations are also mentioned for a quick analysis of the contemporary techniques employed in the domain.

Le et al. proposed a multitask network which is formed as a cascaded structure. The model consists of two targets, i.e., (i) effectively differentiate the brain tumor regions and (ii) estimate the brain tumor mask. The first objective is performed by our proposed contextual brain tumor detection network, which plays a role of an attention gate and focuses on the region around brain tumor only while ignoring the far neighbor background which is less correlated to the tumor. Different from other existing object detection networks which process every pixel, the contextual brain tumor detection network only processes contextual regions around ground-truth instances and this strategy aims at producing meaningful regions proposals. The second objective is built upon a 3D atrous residual network and under an encode-decode network in order to effectively segment both large and small objects (brain tumor).

Ghassemi et al proposed a new deep learning method for tumor classification in MR images. A deep neural network is first pre-trained as a discriminator in a generative adversarial network (GAN) on different datasets of MR images to extract robust features and to learn the structure of MR images in its convolutional layers. Then the fully connected layers are replaced and the whole deep network is trained as a classifier to distinguish three tumor classes. The deep neural network classifier has six layers and about 1.7 million weight parameters. Pre-training as a discriminator of a GAN together with other techniques such as data augmentations (image rotation and mirroring) and dropout prevent the network from overtraining on a relatively small dataset.

Amin et al. proposed that Brain tumor occurs because of anomalous development of cells. It is one of the major reasons of death in adults around the globe. Millions of deaths can be prevented through early detection of brain tumor. Earlier brain tumor detection using Magnetic Resonance Imaging (MRI) may increase patient's survival rate. In MRI, tumor is shown more clearly that helps in the process of further treatment. This work aims to detect tumor at an early phase. The proposed approach is evaluated in terms of peak signal to noise ratio (PSNR), mean squared error (MSE) and structured similarity index (SSIM) yielding results as 76.38, 0.037 and 0.98 on T2 and 76.2, 0.039 and 0.98 on Flair respectively. The segmentation results have been evaluated based on pixels, individual features and fused features. At pixels level, the comparison of proposed approach is done with ground truth slices and also validated in terms of foreground (FG) pixels, background (BG) pixels, error region (ER) and pixel quality (Q). The approach achieved 0.93 FG and 0.98 BG precision and 0.010 ER on a local dataset.

Manogaran et al. proposed an improved orthogonal gamma distribution-based machine-learning approach is used to analyze the under- segments and over-segments of brain tumor regions to automatically detect abnormalities in the ROI. Further data imbalances due to improper edge matching in the abnormal region is sampled by matching the edge coordinates and sensitivity, and the selectivity parameters are measured using the machine learning algorithm. The benchmark medical image database was collected and analyzed to validate the efficiency and accuracy of the optimal automatic detection in tumor and non-tumor regions. The mean error rate of the algorithm was determined using a mathematical formulation. The system is evaluated based on experimental results that showed the method of orthogonal gamma distribution with the machine learning approach attained an accuracy of 99.55% in detecting brain tumors. This research contributes to the field of brain abnormality detection and analysis without human intervention in the health care sector.

Chato et al. proposed a method to automatically predict the survival rate of patients with a glioma brain tumor by classifying the patients MRI image using machine learning (ML) methods. The dataset used in this study is BraTS 2017, which provides 163 samples; each sample has four sequences of MRI brain images, the overall survival time in days, and the patients age. The dataset is labeled into three classes of survivors: short-term, mid-term, and long-term. To improve the prediction results, various types of features were extracted and trained by various ML methods. Features considered included volumetric, statistical and intensity texture, histograms and deep features; ML techniques employed included support vector machine (SVM), k-nearest neighbors (KNN), linear discriminant, tree, ensemble and logistic regression. The best prediction accuracy based on classification is achieved by using deep learning features extracted by a pre-trained convolutional neural network (CNN) and was trained by a linear discriminant.

Hasan et al. proposed an Automatic detection and categorization has several advantages over the manual counterpart. Authors here put forth that accurate automatic detection and class of picture could be very tough challenge whether or not they may be medical photos containing tumors interior human brain or other herbal photographs. His work gives a hybrid device for diagnosing diseases (automated category) via utilizing the MRI images. MRI images along with the natural images which is considered very important for human life. This work provides an efficient and fast way for brain tumor treatment diagnosis. This proposed system comprises broadly three steps: the first step being pre-processing image. Subsequently Discrete Wavelet Transform is employed prior to feature extraction. Finally the category of the tumor is categorized using a Probabilistic Neural Network. The algorithm is applied on 35 MRI brain images from different types were utilized as testing data phase. The result represents that 32 images are categorized aptly and the rest 3 images are not classified correctly. The system classification proved its effectiveness to classify MRI brain normal and tumors type. The accuracy percentage of classification Utilizing PNN is figured out to be nearly 91 %.It was founding the paper.

III. PERFORMACNE METRICS

The performance metrics of the classifiers are generally computed based on the true positive (TP), true negative (TN), false positive (FP) and false negative (FN) values which are used to compute the accuracy and sensitivity of the classifier, mathematically expressed as:

$$\boldsymbol{Ac = \frac{TP+TN}{TP+TN+FP+FN}} \quad \textbf{(6)}$$

Sensitivity: It is mathematically defined as:

$$Se = \frac{TP}{TP+FN} \quad (7)$$

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

$$Precisiosn = \frac{TP}{TP+FP} \quad (9)$$

$$F - Measure = \frac{2.Precision.Recall}{Precision+Recall} \quad (10)$$

The aim of any designed approach is to attain high values of accuracy of classification along with other associated parameters. The computation complexity of the system often evaluated in terms of the number of training iterations and execution time is also a critically important metric which decides the practical utility of any algorithm on hardware constrained devices.

CONCLUSION:

It can be concluded that It can be concluded that AI based techniques can prove to be a strong supporting tool to medical practitioners aiming to detect brain tumor cases. Development of such techniques are not aimed at replacing doctors, rather supporting and augmenting them. Several AI and ML based techniques have been proposed with their own strengths and limitations. Different stages of the data processing and segmentation have been enlisted. The significance of different image features and extraction techniques have been clearly mentioned with their utility and physical significance. Various machine learning based classifiers and their pros and cons have been highlighted. The mathematical formulations for the feature extraction and classification gave been furnished. A comparative analysis of the work and results obtained has been cited in this paper. It can be concluded that image enhancement and feature extraction are as important as the effectiveness of the automated classifier, hence appropriate data processing should be applied to attain high accuracy of classification.

Some of the future directions of work can be separate image enhancement and data optimization to avoid both over fitting and under-fitting, moreover, employing separate image denoising to extract features more accurately. Solely computing feature based on deep learning architecture can be compared with statistical feature extraction. This would make the system application to a large variety of datasets. Moreover, classifiers which do not saturate in terms of performance with increasing sat size can be employed.

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