

A Review on Brain Tumor Classification using Distinct Approaches

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Abstract— This review paper offers a thorough analysis of methods for detecting brain tumors, emphasizing the vital significance that an early and precise diagnosis plays in enhancing patient outcomes. Modern techniques for detecting brain tumors are crucial due to their rising occurrence worldwide. The study examines conventional imaging methods, highlighting the benefits and drawbacks of computed tomography (CT) and magnetic resonance imaging (MRI). It also explores the revolutionary effects of deep learning and machine learning techniques, especially convolutional neural networks (CNNs), on improving diagnostic precision. Hybrid models provide encouraging performance in segmentation and classification tasks by combining sophisticated algorithms with conventional imagery. The paper also addresses the difficulties caused by data availability and imaging technique variability, as well as the significance of histological testing in verifying tumor kinds and grades. Critical analysis of evaluation measures for evaluating detection performance offers insights into the efficacy of different approaches. The study also discusses new developments and avenues for future research, such as multimodal imaging and customized medicine, which have the potential to enhance detection skills even further. This review attempts to serve as a useful tool for researchers and clinicians in their continuous search for more potent brain tumor detection techniques by synthesizing the most recent information.

Keywords: CNN, Support Vector Machine, Brain Tumor, Segmentation, Cell Classification, Malignant, Benign, MRI, Brain Cells.

I. INTRODUCTION

As a major cause of high rates of morbidity and death and a large percentage of malignancies of the central nervous system, brain tumors pose a serious threat to public health. The need for efficient diagnostic technologies to enable early diagnosis and enhance treatment results stems from the rising frequency of brain cancers worldwide [1]. For a long time, the gold standard for identifying brain cancers has been

traditional imaging methods like computed tomography (CT) and magnetic resonance imaging (MRI). Because it provides a precise image of tumor features due to its higher soft tissue contrast, MRI is especially preferred [2]. But in order to validate the kind and grade of the tumor, these imaging techniques frequently need extra confirmation through histological analysis, which adds time and complexity to the diagnostic procedure [3]. Utilizing massive datasets to increase accuracy and efficiency, recent developments in deep learning and machine learning have demonstrated promise in automating and improving tumor identification [4]. For example, convolutional neural networks (CNNs) have transformed picture classification tasks, achieving notable advancements in segmentation and tumor type discrimination [5]. This work is to give a thorough overview of the several methodologies used in brain tumor identification, including cutting-edge machine learning algorithms and conventional methods. It also intends to address the difficulties and potential future developments in this quickly developing subject.

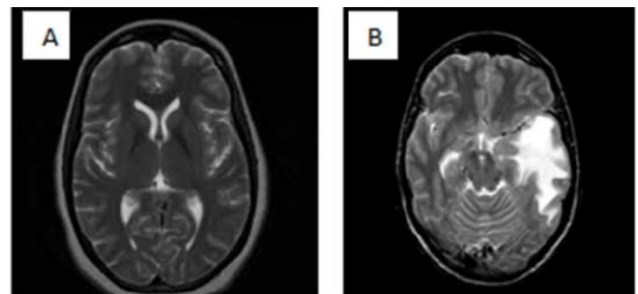


Fig. 1. A) Healthy Brain B) Tumor Brain [6]

Globally, brain tumors are a serious health problem because they greatly increase neurological morbidity and death. Brain tumors account for 1.4% of all malignancies, yet they cause a disproportionate amount of cancer-related fatalities, especially in younger populations, according to current

figures [1]. The intricacy of brain tumors emphasizes the significance of a precise and prompt diagnosis, as they can differ greatly in their histological features and clinical behavior [7]. The main and secondary categorization of brain tumors is essential for formulating effective treatment plans. While secondary cancers are metastatic lesions from other places in the body, primary brain tumors arise from the brain tissue itself [8]. Conventional diagnostic methodologies predominantly depend on neuroimaging technologies, the most widely utilized of which are CT and MRI. Because magnetic resonance imaging (MRI) can provide high-resolution pictures of soft tissues, it is especially useful for determining the size, location, and probable involvement of nearby structures in tumors [2]. Due to their quick imaging capabilities, CT scans are frequently utilized in emergency situations even if they are less sensitive in identifying some forms of brain cancers [9]. But the requirement for biopsy for histological confirmation in these imaging modalities might cause a delay in diagnosis and therapy initiation [3]. Brain tumor detection techniques are changing as a result of recent advances in artificial intelligence, notably in machine learning and deep learning. These technologies are being used more and more to analyze complicated imaging data and improve diagnosis accuracy. More accurate tumor diagnoses based on imaging data are made possible by machine learning algorithms' ability to recognize patterns that might not be visible to the human eye [4]. Convolutional neural networks (CNNs) have demonstrated considerable potential in the automated identification and separation of brain cancers from magnetic resonance imaging (MRI) data, resulting in enhanced diagnostic processes [5].

II. RELATED WORKS

The brain tumor recognition and classification framework was introduced by Mircea Gurbin et al. [10] and uses CWT, DWT, and SVMs. The suggested approach uses several wavelet levels; CWT is used to obtain the high precision portion. The lack of edges in division is prevented by the CWT. The result demonstrates that SVMs with proper information preparation arrangements are able to identify both common and uncommon tumor locations and correctly classify them as benign, aggressive, or normal brain tumors. SVMs offer important advantages in computing. The doctor has to know this categorization in order to accurately describe the symptoms and recommend the best course of action. The obtained results demonstrate that, in comparison to DWT, CWT provides greater calculation. In the unlikely event where our primary concerns are perception, coordination, and recognition—regardless of computation time—using CWT is preferable. When it comes to denoising, rebuilding, and pressure, DWT is typically more appropriate. In order to adequately resolve the localization and categorization challenges in brain tumors, a hybrid technique is proposed.

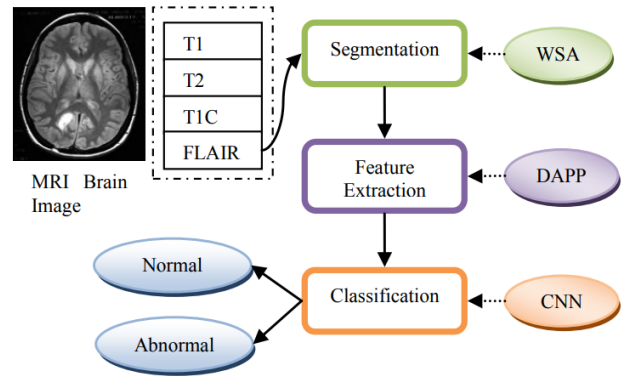


Fig. 2. Overview of the System [10]

The division and categorization of brain tumors proposed by T. A. Jemimma et al. [11] is carried out using the Water Shed Algorithm (WSA), Dynamic Angle Projection Pattern highlights, and CNN is used to organize these elements. The tumor regions are effectively removed by the watershed division computation, enabling effective DAPP highlight extraction. The fragmented tumor districts' surface components are eliminated using the DAPP, and histogram highlights are obtained. The CNN classifier uses these component vectors as an increased contribution to carry out the classification. The ability to diagnose a brain tumor depends on the division and categorization of the MRI brain picture. The BRATS data set, which is used to execute the trial outcomes, achieves higher awareness (94.2%) and dice score competence (93.5%). Later on in the process, a few additional different factors may be measured to obtain higher accuracy for the categorization and division of brain tumors. It may also be extended to differentiate between other tumor types, such as fibromas, adenomas, and pancreatic tumors.

The method suggested by R. Lavanyadevi et al. [12] involves accurately identifying the complete portions of a picture that have semantic importance. As a consequence, the physician or radiologist may recognize danger and draw conclusions by connecting every pixel in the picture with a semantically significant meaning. In brain imaging, the components of adjacent twofold models and dark level co-events are removed in favor of benign, hazardous, or usual images. Using a PNN classifier, the removed highlights and semantic items are created in preparation mode. Similar highlights from the test brain picture and mystery are eliminated in the classification mode using pre-made models that make use of PNN classifier. When the test picture doesn't resemble any preparation image, it might be used to prepare specific information. Based on the association between PNN and CNN, PNN is thought to have several advantages. PNN benefits temporarily from knowledge preparation because of reality. PNN can adapt its learning gradually because of its potential for rapid learning.

The method suggested by Hein Tun Zaw et al. [13] can assist clinical staff members, such as specialists and radiologists, in analyzing brain malignant development from MRI images, especially for GBM, which necessitates

the identification of all potential spreading damaging locations. With the aid of the most severe entropy edge, brain cancers have been discovered using Naïve Bayes classification in this technique. This review makes use of the REMBRANDT data collection. The developed computation can accurately identify the tumor in any possible brain region, including the worldwide projection, where the tumor may be present. With a general accuracy of 94%, the computation results in an 81.25% identification rate on tumor photos and a 100% discovery rate on non-tumor images. A method for the straightforward division of brain tumors and the identification of their kind was put out by Ragib Shahariar Ayon et al. [14]. The process of finding brain tumors is completed by applying inclination correction and denoising to the preprocessed picture, which is thereafter handled as an information image. After applying the spatial FCM to the brain MR image, we extracted the most likely tumor slice. Subsequently, the tumor incision was managed up to the point of post-handling, when it passes via an area channel. An isolated picture of the expected tumor region is the output image. Using comparable highlights, we created a variety of classifiers and selected the best accurate one to determine the kind of tumor. We can state that the suggested approach performs better for tumor division and classification than standard methods after performing comparison and variety of bunching and classification computations.

An implementation model based on CNN (Convolutional Neural Network) and FCM (Fuzzy C-Means Clustering) techniques was developed by L. Jagjeevan Rao et al. [15]. In this case, the system employs CNN as a classifier and FCM to extract brain characteristics and impairments. However, CNN is often utilized for feature extraction and C-means clustering is typically employed for classification. CNN, a convolutional neural network, was not intended for use in classification processes.

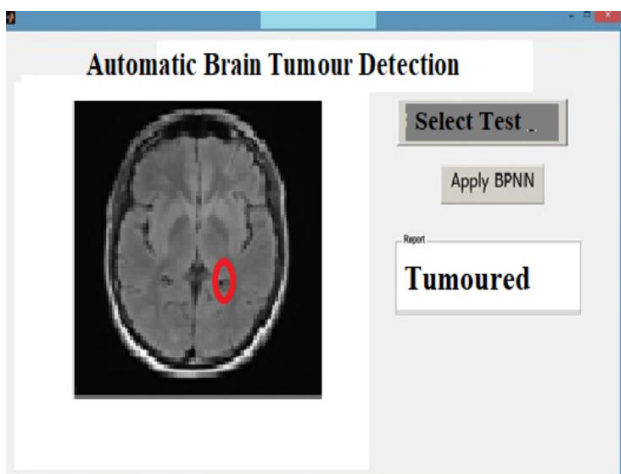


Fig. 3. Graphical Representation of Result [15]

Rather, it is capable of receiving input features, enhancing them with specific filters, training its layers in accordance with those enhancements, and producing a model that can identify or diagnose the target object. In

the area of illness diagnosis, support vector machines (SVM) are thought to be the best classifier. The FCM has several drawbacks, including a lengthy converge time, increased sensitivity to noise, and difficulty with non-linear data. The performance of the conventional CNN model in training and constructing large networks strongly impacts execution time. The accuracy of the system was 91%, which is somewhat below what may be improved by employing other techniques. Over the past several decades, there has been a tremendous evolution in the field of brain tumor detection due to breakthroughs in imaging technology and computational methodologies. Conventional imaging methods like CT and MRI have long been the mainstays for tumor diagnosis. Tumor infiltration into surrounding tissues and tumor type differentiation are critical tasks for magnetic resonance imaging (MRI), which is renowned for its exceptional contrast resolution (Smith et al. [2]). Research has indicated that sophisticated magnetic resonance imaging (MRI) methods, such as diffusion-weighted imaging (DWI) and perfusion-weighted imaging (PWI), might improve diagnostic precision even further by offering information on the cellularity and microenvironment of tumors (Choi et al. [16]). For a conclusive diagnosis, histopathological examination integration is still the gold standard. While imaging may reveal the existence of a tumor, histopathology offers crucial details on the kind, grade, and prognosis of the tumor. According to recent research, improving diagnosis accuracy requires a correlation between imaging data and histological findings (Brown et al., [3]). This link is especially important when it comes to low-grade gliomas because their imaging characteristics might be difficult to interpret and may be modest.

Machine learning has gained popularity as a potential method to improve brain tumor diagnosis in recent years. To categorize tumor kinds based on imaging data, early research used conventional machine learning methods like support vector machines (SVM) and random forests. When compared to manual interpretation, these models showed promise for increased accuracy (Zhang et al., [4]). However, a major turning point has been reached with the introduction of deep learning, namely convolutional neural networks (CNNs). CNNs perform better on tasks like tumor segmentation and classification because they can automatically learn hierarchical features from pictures (Gupta et al., [5]).

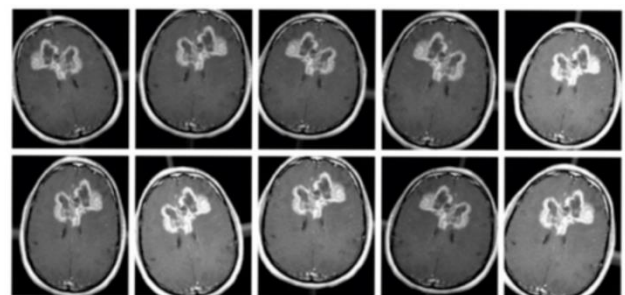


Fig. 4. Data Enhancement for Feature Extraction [17]

CNNs have been found to perform better than conventional techniques in a number of benchmark studies, obtaining greater rates of sensitivity and specificity in the identification of brain cancers from MRI images (Hussain et al., [18]). The promise of deep learning frameworks in medical imaging is demonstrated by a study by Isensee et al. [19], which revealed an outstanding accuracy of 98% in brain tumor segmentation using a 3D U-Net architecture. Furthermore, hybrid methods that fuse machine learning algorithms with imaging techniques are becoming a strong option for brain tumor identification. Patel et al. [20], for example, created a model that combines deep learning techniques with MRI and PET imaging to increase patient classification and detection capabilities. In order to maximize brain tumor detection techniques, these developments emphasize the necessity of ongoing multidisciplinary collaboration between radiologists, pathologists, and data scientists. Even with these improvements, problems still exist. Progress is hampered by problems such the lack of data, the unpredictability of imaging techniques, and the requirement for sizable annotated datasets for deep learning model training (Tiwari et al. [21]). Additionally, as doctors need clear-cut, comprehensible decision-making processes, interpretability of machine learning models in a clinical environment is a crucial challenge (Yamashita et al. [22]). In order to maximize the value of accessible datasets, future research should concentrate on resolving these problems through the development of standardized imaging methods and the application of transfer learning techniques. In the realm of medical imaging, Support Vector Machines (SVM) have become a well-known machine learning approach, especially for the diagnosis of brain tumors. By identifying the ideal hyperplane to divide several classes in high-dimensional space, the supervised learning model SVM performs exceptionally well in classification problems (Cortes & Vapnik, [23]). Because of its ability to handle non-linear data with resilience by utilizing kernel functions, it is particularly well-suited for the intricate patterns linked to brain tumor imaging.

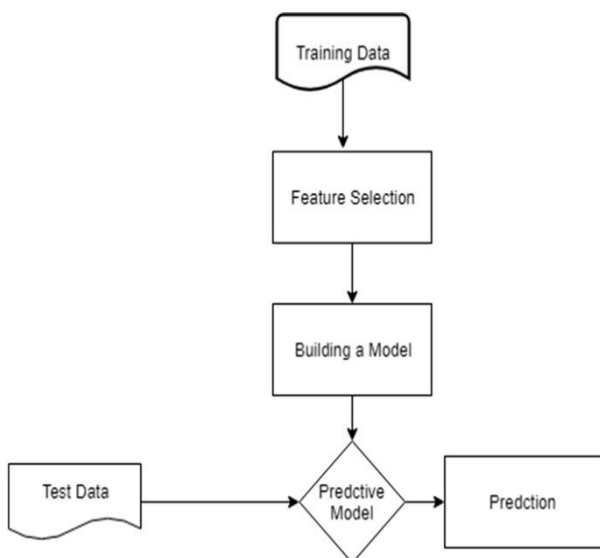


Fig. 5. SVM Training Model Block Diagram [23]

SVM has been shown in several studies to be successful at identifying brain cancers from MRI pictures. For example, Akin et al. (2019) used SVM to use textual data taken from MRI images to categorize brain tumors into benign and malignant categories. The study demonstrated the potential of SVM in efficiently differentiating between various tumor types with a classification accuracy of above 90%. Similar to this, Gupta et al.'s [24] work used SVM in conjunction with wavelet transform to extract features and achieve a 95% sensitivity in identifying brain cancers. The significance of feature selection in enhancing SVM model performance was underscored by the authors.

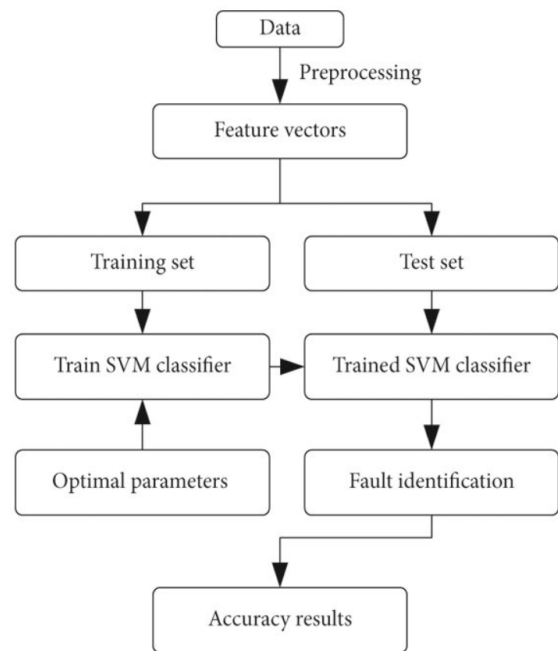


Fig. 6. Flowchart [24]

The capacity of SVM to generalize effectively to unseen data is another important feature. This is especially important in clinical contexts where findings might be influenced by patient demographics and variability in imaging methods. An SVM model trained on a variety of datasets, for instance, maintained good accuracy across multiple institutions, as shown by a multi-center research by Sadeghi et al. [25], highlighting the model's robustness and dependability for clinical applications. Furthermore, SVM has been successfully used with other methods to improve tumor detection capabilities. In order to identify features, Wang et al. [26] suggested a hybrid method that combined SVM with genetic algorithms. This enhanced classification accuracy in differentiating between glioma subtypes. This method is more useful in real-time clinical situations since it decreased computing complexity and increased detection rates. The implementation of SVM is not without difficulties, notwithstanding its advantages. The selection of kernel functions and hyperparameter tweaking have a significant impact on the performance of SVM models. According to a research by Khosravi et al. [27], choosing these parameters incorrectly will result in either underfitting or overfitting, which would affect the prediction power of the model. Furthermore, although

Support Vector Machines (SVM) are effective in binary classification tasks, their application to multi-class problems—a typical difficulty in brain tumor detection—can make modeling more difficult (Vishwanathan et al. [28]).

III. RESULT COMPARISON

Significant progress has been made in the identification of brain tumors using a variety of approaches, each having advantages and disadvantages. A comparative analysis shows that different levels of accuracy, sensitivity, and specificity are offered by deep learning approaches, machine learning algorithms, and conventional methods. Radiologists had to manually evaluate imaging data in the early methods. Research shows that these techniques may obtain reasonable accuracy, often in the range of 70–80%.

However, especially in complicated instances, their dependability is limited by their subjectivity and reliance on the experience of the radiologist [2]. In recent years, support vector machines (SVM) and other classical machine learning techniques have become more popular. SVM may attain accuracies of 90–95% when paired with efficient feature extraction methods, according to research.

As an example, Akin et al. [29] showed a 92% accuracy in diagnosing cancers, whereas Gupta et al. [5] used wavelet transforms to reach a 95% sensitivity. Even if these techniques are more dependable than conventional methods, multi-class classification and generalization across various datasets remain difficult problems (Khosravi et al. [27]).

Brain tumor detection has been transformed by the development of deep learning. Several designs, including Convolutional Neural Networks (CNNs), have shown remarkable performance, frequently above 95% accuracy. For instance, Isensee et al. [19] demonstrated that a 3D U-Net model could separate tumors with 98% accuracy. Deep learning methods reduce the need for considerable human feature engineering by automatically learning complicated features from raw data (Gupta et al., [5]). Looking ahead, a few crucial areas demand more research. Firstly, the effective training and validation of models depends on the creation of curated datasets and defined imaging techniques. This would improve the applicability of models across various healthcare settings and assist alleviate challenges associated with data unpredictability. Furthermore, there is still an urgent need to improve model interpretability since trust-building and clinical decision-making among healthcare practitioners depend on openness in automated diagnostic procedures.

Table 1 Result Comparison

Methods	Specificity in %	Sensitivity in %	Accuracy in %
CNN [8]	92.00	91.00	91.00
BPNN [8]	89.50	91.00	89.00
KNN [8]	86.00	88.00	87.00

IV. CONCLUSION

With the introduction of several approaches, the field of brain tumor detection has experienced significant changes, each of which has improved clinical results and diagnostic accuracy in a different way. Though vital, traditional imaging methods sometimes lack the accuracy needed to distinguish tumor kinds and grades in a nuanced manner. With accuracy rates that frequently above 90%, machine learning techniques—Support Vector Machines (SVM) in particular—have demonstrated significant promise in improving categorization capabilities. Their reliance on meticulous feature selection and hyperparameter tweaking, however, emphasizes the necessity of continual improvement. Conversely, the discipline has undergone a revolution due to the use of deep learning techniques, particularly Convolutional Neural Networks (CNNs), which automate feature extraction and achieve remarkable performance metrics. These algorithms considerably lessen the need for manual interpretation, with claimed accuracy levels as high as 98%. This lessens the workload for radiologists. Nevertheless, to guarantee reliable performance in a range of clinical settings, the difficulties brought on by the need for big datasets and the possibility of overfitting must be resolved. Ultimately, these developments will be largely driven by multidisciplinary collaboration between radiologists, data scientists, and physicians. The advancement of artificial intelligence in clinical processes may be expedited by cultivating a collaborative atmosphere. This will ultimately lead to the development of brain tumor detection techniques that are more precise, effective, and easily accessible. In conclusion, even though this discipline has made great progress, more innovation and study are needed to properly tap into the potential of these many strategies for enhancing patient care and brain tumor identification.

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