International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 2, Mar-Apr-2026, ISSN (Online): 2395-566X

Brain Tumor Detection and Classification Using Machine Learning

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Abstract- Brain tumors are among the most critical neurological disorders and require early and accurate diagnosis to improve patient survival rates. Traditional methods of tumor detection rely heavily on manual analysis of medical images such as Magnetic Resonance Imaging (MRI), which can be time-consuming and prone to human error. This study presents a machine learning–based approach for the automated detection and classification of brain tumors from MRI images. The proposed system utilizes image preprocessing techniques to enhance image quality and remove noise, followed by feature extraction to identify significant patterns associated with tumor regions. Various machine learning algorithms, such as Support Vector Machines (SVM), Random Forest, and Convolutional Neural Networks (CNN), are applied to classify MRI images into tumor and non-tumor categories, and further categorize tumor types. The model is trained and evaluated on a labeled MRI dataset to ensure accuracy and reliability. Experimental results demonstrate that the proposed method improves diagnostic efficiency and achieves high classification accuracy compared to traditional approaches. This automated system can assist radiologists and healthcare professionals in early tumor detection, reducing diagnosis time and improving treatment planning.

Keywords- Brain Tumor Detection, Machine Learning, MRI Image Analysis, Image Processing, Tumor Classification, Convolutional Neural Networks (CNN), Support Vector Machine (SVM), Feature Extraction, Medical Image Analysis, Artificial Intelligence in Healthcare.

I. INTRODUCTION

Brain tumors are abnormal growths of cells within the brain that can significantly affect the normal functioning of the nervous system. They can be classified as benign (non-cancerous) or malignant (cancerous), and their early detection is crucial for effective treatment and improved patient survival rates.

Medical imaging techniques such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans are widely used by radiologists to identify and analyze brain tumors. However, manual analysis of these images can be time-consuming, complex, and subject to human error, especially when dealing with large volumes of medical data.

The central nervous system (CNS) plays a crucial role in transmitting sensory information and coordinating responses throughout the human body [1,2,3]. It consists primarily of the brain and spinal cord, which together regulate most physiological and cognitive activities. The brain is the most complex organ of the human body and is responsible for controlling thought, movement, memory, and sensory processing. Anatomically, the brain is divided into three main parts: the brain stem, cerebrum, and cerebellum [4].

The average weight of a normal human brain is approximately 1.2–1.4 kg, with an average volume of about 1260 cm^3 in males and 1130 cm^3 in females [5]. The cerebrum is the largest part of the brain and is responsible for higher cognitive functions. It is divided into four lobes: the frontal, parietal, temporal, and occipital lobes.

The frontal lobe is responsible for problem-solving, motor control, and decision-making processes, while the parietal lobe manages body position and spatial awareness. The temporal lobe controls memory and auditory processing, and the occipital lobe is primarily responsible for visual processing. The outer layer of the cerebrum, known as the cerebral cortex, is composed of grey matter consisting of densely packed cortical neurons [6].
The cerebellum, although smaller than the cerebrum, plays a vital role in motor control and coordination. It ensures the

systematic regulation of voluntary movements and helps maintain balance and posture.

Compared to other species, the human cerebellum is highly developed and structurally complex [7]. The cerebellum consists of three lobes: the anterior lobe, posterior lobe, and flocculonodular lobe. A round structure called the vermis connects the anterior and posterior lobes. Structurally, the cerebellum contains an inner region of white matter surrounded by an outer grey matter cortex, which is thinner than that of the cerebrum.

The anterior and posterior lobes assist in coordinating complex motor movements, while the flocculonodular lobe plays a key role in maintaining body balance [4,8].

The brain stem is a stem-like structure approximately 7–10 cm in length that connects the brain to the spinal cord. It contains cranial and peripheral nerve bundles and regulates several essential bodily functions such as breathing, eye movement, and balance.

Neural pathways originating from the cerebrum's thalamus pass through the brain stem before reaching the spinal cord, allowing signals to be transmitted throughout the body. The brain stem consists of three main parts: the midbrain, pons, and medulla oblongata.

The midbrain is responsible for motor control and visual and auditory processing, the pons facilitates breathing and communication between different brain regions, and the medulla oblongata regulates vital functions such as blood circulation, swallowing, and reflex actions like sneezing [9].

Brain tumors are graded into four different categories:

- **Grade I:** These tumors do not spread quickly and develop slowly. These are connected to a higher chance of enhanced order and may be surgically eliminated nearly entirely. One such tumor is a pilocytic astrocytoma.
- **Grade II:** Although they may migrate to surrounding tissues and advance to higher grades, these tumors also grow over time. These tumors may detect even though treatment is taken by the patient. An oligodendroglioma tumor is an example of an overtime growth tumor.
- **Grade III:** The growth of these tumors has been quicker than grade II malignancies and could spread to adjoining tissues. Such tumors require post-operative chemo or radiotherapy because surgery alone would be insufficient to treat them. Aden squamous astrocytoma is an indication of such a tumor.
- **Grade IV:** The most dangerous and likely to spread malignant tumors are in this category. They might even use blood vessels to speed up their growth. An illustration of one of these tumors is glioblastoma multiforme [10].

II. RELATED WORK

In this section we are studied previous researches works about brain tumor detection using ML models. we have summarized some previous works.

- Almadhoun et al. [12] proposed a deep educational model using an MRI dataset for brain tumor detection. In addition to the deep educational model, they applied four other transfer learning models: VGG16, MobileNet, ResNet-50, and Inception V3. They used a dataset of 10,000 MR images with a 200 × 200 pixel resolution to evaluate their models. The dataset was divided into two categories with 5000 images each: brain tumors and non-brain tumors. Their proposed model, the deep educational model, performed better; the training accuracy was 100%, and the test accuracy was 98%.
- Musallam et al. [11] introduced a DCNN model using an MRI dataset for detecting brain tumors. In their proposal, a lightweight model with a few convolutions, max-pooling, and iterations was used. The researchers also analyzed VGG16, VGG19, and CNN-SVM.
- Glioma (934), meningioma (945), no tumor (606), and pituitary(909) were the four subcategories of the 3394 MR images. The suggested model achieved an overall accuracy of 97.72%, a detection rate of 99% for glioma, a detection rate of 98.26% for meningioma, a detection rate of 95.95% for pituitary, and a detection rate of 97.14% for normal images.
- Nayak et al. [13] proposed dense EfficientNet, which is a CNN-based network, to detect brain tumor images using MRI. The researchers also analyzed ResNet-50, MobileNet, and MobileNetV2, with their dense EfficientNet performing better. They obtained a 98.78% accuracy and a 98.0% F1-score after training the dense EfficientNet model. Four different types of MRI were employed in their research to identify brain tumors. The total dataset comprised 3260 MR images.

- Khalil et al. [15] proposed a modified two-step dragonfly algorithm for brain tumor segmentation using 3D MR images. The greatest difficulties in identifying and segmenting the early stages of brain tumors are variations in the tumor size and structure. To overcome these challenges, the researchers employed a two-step dragonfly algorithm to precisely extract the original contour point. To obtain the results using the proposed model, they used BRATS 2017 3D MR brain tumor dataset. They achieved an accuracy that was about 5% higher than that of the previous researchers, who performed a nearly identical study. To validate their findings, they also applied a variety of techniques, including fuzzy C-means, SVM, and random forests. To evaluate their results, they considered the metrics of the accuracy, precision, and recall. After evaluating their proposed model, they obtained an accuracy of 98.20%, a recall of 95.13%, and a precision of 93.21%, which were better than the other models. The main weakness in this study was that the researchers only focused on the entire tumor segment, and they did not takeinto account many tumors per slice.
- In this study, different types of brain tumor MRI images were collected to evaluate the performance of the proposed Convolutional Neural Network (CNN) model. To assess the effectiveness of the proposed approach, several machine learning models were also considered for comparison. The experimental results demonstrated that the proposed CNN model achieved better performance compared to the transfer learning models used in this study. However, previous studies have reported promising results using transfer learning models, achieving accuracy levels above 90% [44]. This observation highlights the need for further investigation, which will be considered in future research.

Unlike many existing studies that rely on relatively small datasets, this research utilized a larger dataset consisting of 3264 MRI images, providing a more comprehensive evaluation of the proposed model. During the initial stage of experimentation, the system required a longer processing time due to limited GPU resources. However, through optimization and system improvements, the training time was significantly reduced. Although several previous studies have reported certain limitations in brain tumor detection approaches, the proposed method aims to address these issues by improving classification performance, reducing training time, and enhancing overall model efficiency.

III. FINDINGS

Expert radiologists usually perform brain tumor segmentation and classification manually. However, Machine Learning (ML) and Deep Learning (DL) techniques can help radiologists make more accurate and faster decisions. This study reviews current automated methods used for brain tumor classification.

MRI images are first preprocessed using techniques such as histogram equalization, median filtering, Gaussian filtering, and Wiener filtering to improve image quality. Different segmentation methods are used to detect tumor regions, including clustering-based, statistical, CNN-based, region-based, and threshold-based techniques. Among these, clustering algorithms such as K-means and C-means and adaptive global thresholding are commonly used. Deep learning-based segmentation methods can identify tumor regions more accurately.

Feature extraction is an important step in tumor detection. Techniques such as Gray Level Co-occurrence Matrix (GLCM) and Discrete Wavelet Transform (DWT) are widely used. GLCM extracts texture-related features, while DWT extracts approximation coefficients from the images. In deep learning models, feature extraction is performed automatically by the network using architectures such as ResNet.

Feature selection and dimensionality reduction are also important because selecting the best features for classification is challenging. Techniques such as Principal Component Analysis (PCA) and bio-inspired algorithms like Particle Swarm Optimization (PSO) are used to reduce the number of features. In many cases, hybrid methods combining multiple features are used to improve classification performance.

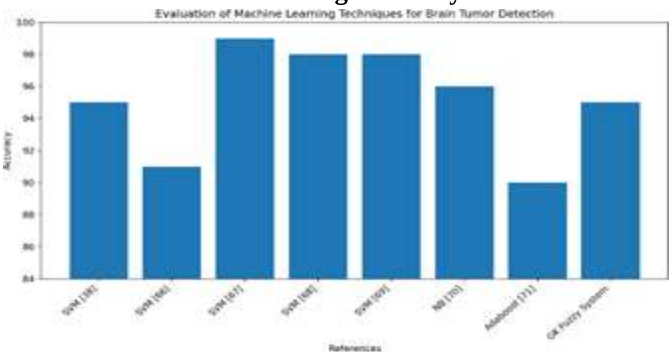
Both ML and DL models are applied for tumor classification. For example, multi-kernel Support Vector Machine (SVM) classifiers use different kernels such as linear, radial basis function (RBF), and cubic kernels for binary classification. Some hybrid approaches such as ANFIS (Adaptive Neuro-Fuzzy Inference System), which combines fuzzy logic with neural networks, have shown better performance for binary classification tasks.
However, many studies face limitations because available datasets do not include all tumor types and grades. Researchers often need to collect MRI images from hospitals, making it

difficult to compare different methods. Therefore, a standardized and comprehensive database containing all tumor types would be useful for future research.

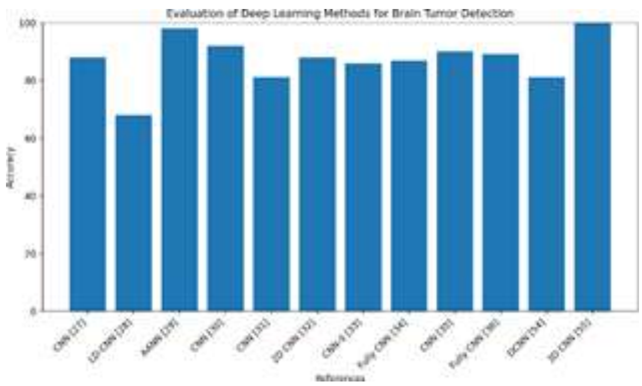
Deep learning methods can extract more detailed features from large datasets, which improves tumor segmentation and classification. Transfer learning techniques also help improve prediction accuracy. Machine learning methods work well when the dataset is small, while deep learning models perform better when large datasets are available.

Machine learning approaches require several preprocessing steps such as filtering, intensity correction, and skull stripping to preserve important visual information in the images. However, ML models can become complex because they require many parameters, which increases computation time and system requirements. In contrast, deep learning models are less dependent on manual feature extraction because the network automatically learns important features from the data. Overall, research shows that both machine learning and deep learning approaches achieve high accuracy in brain tumor detection and classification.

Machine Learning Accuracy Chart



Deep Learning Accuracy Chart



DataSets used:
In this research, Magnetic Resonance Imaging (MRI) datasets were used to develop and evaluate the proposed brain tumor detection and classification model. MRI is widely used in medical imaging because it provides high-resolution images of brain tissues and allows accurate identification of abnormal regions such as tumors.

The dataset used in this study consists of 3264 brain MRI images collected from publicly available sources. These images represent four categories of brain conditions: glioma tumor, meningioma tumor, pituitary tumor, and normal (no tumor) cases. The dataset was selected because it contains different tumor types, allowing the model to perform both tumor detection and multi-class classification tasks.

Before training the model, the dataset was divided into three parts: training, validation, and testing datasets. Approximately 80% of the images were used for training, while the remaining 20% were used for testing and validation to evaluate the performance of the model. Data augmentation techniques such as image rotation, flipping, and scaling were also applied to increase the diversity of the dataset and reduce the risk of overfitting.

To ensure better model performance, preprocessing techniques were applied to the MRI images. These included image resizing, normalization, noise removal, and intensity adjustment. These preprocessing steps improved image quality and helped the model focus on important features related to tumor regions.

1. Data Collection
The first step of the methodology involves collecting MRI brain images from publicly available datasets. The dataset used in this study contains 3264 MRI images representing different categories such as glioma tumor, meningioma tumor, pituitary tumor, and normal brain images. These images are used to train and evaluate the proposed model.

2. Image Preprocessing

II. TUMOR Classification Approaches
The input data is sorted using classification techniques into a variety of separate classes., after which training and validation are carried out using both known and unknown instances.

The classification of tumors into relevant classifications is a widespread application of machine learning, tumor as well as non-tumor, and malignant and benign tumors.

Tumor Type	Number of Images
Glioma Tumor	926
Meningioma Tumor	937
Pituitary Tumor	901
No Tumor	500
Total	3264

Supervised methods include KNN, support vector machine, nearest subspace classification model, and representation classification model. Fuzzy C Means, hidden Markova random field, and self-organization map, are examples of unsupervised approaches .

IV. METHODOLOGY

The proposed methodology aims to develop an automated system for detecting and classifying brain tumors from MRI images using machine learning and deep learning techniques. The overall workflow consists of several stages, including data collection, preprocessing, feature extraction, model training, and classification. Each stage plays an important role in improving the accuracy and reliability of the system.

Preprocessing is an essential step to improve the quality of MRI images and remove unwanted noise. In this stage, several preprocessing techniques are applied, including image resizing, normalization, and filtering. Noise removal techniques such as median filtering, Gaussian filtering, and intensity normalization are used to enhance important features of the brain images. These preprocessing steps help the model focus on relevant tumor regions and improve classification performance.

Feature Extraction

Feature extraction is performed to identify meaningful patterns in MRI images. Traditional machine learning approaches use techniques such as Gray Level Co-occurrence Matrix (GLCM) and Discrete Wavelet Transform (DWT) to extract texture and structural features from images. These features represent important characteristics of tumor regions, such as texture, shape, and intensity variations.

In deep learning approaches, feature extraction is performed automatically by Convolutional Neural Networks (CNN). CNN models learn hierarchical image features directly from the input images without requiring manual feature engineering.

Model Training

After preprocessing and feature extraction, the dataset is divided into training and testing sets. Approximately 80% of the images are used for training the model, while the remaining 20% are used for testing and validation. The proposed CNN model is trained using MRI images to learn complex patterns associated with brain tumors.

During the training process, optimization algorithms and activation functions are used to update model parameters and improve learning performance. Data augmentation techniques such as rotation, flipping, and scaling are also applied to increase dataset diversity and prevent overfitting.

Classification

The final stage involves classifying MRI images into different categories based on the trained model. The system predicts whether the MRI image contains a tumor or not, and further classifies the tumor into specific types such as glioma, meningioma, or pituitary tumor. The performance of the model is evaluated using metrics such as accuracy, precision, recall, and F1-score.

The proposed methodology provides an efficient framework for automated brain tumor detection and classification, assisting medical professionals in faster diagnosis and decision-making.

V. CONCLUSIONS AND FUTURE WORKS

Early detection of brain tumors is essential for reducing mortality rates and improving patient outcomes. However, accurate detection remains challenging due to variations in tumor shape, size, and structure. In this study, a deep learning-based approach was proposed for the early detection and classification of brain tumors using MRI images. A Convolutional Neural Network (CNN) model was developed and trained on a large dataset of MRI brain images to automatically learn important features for tumor detection.

The experimental results demonstrated that the proposed CNN model achieved promising performance in identifying brain tumors from MRI images. To ensure reliable evaluation, several performance metrics were used to assess the effectiveness of the model. In addition to the proposed CNN architecture, other machine learning models were also considered to compare the results and validate the performance of the proposed method.

One of the main limitations of this research was the high computational requirement of deep learning models. Since the CNN architecture contained multiple layers and the available GPU resources were limited, the training process initially required a significant amount of time. However, after upgrading the GPU system, the training time was considerably reduced and the overall system performance improved.

In future work, the proposed approach can be further enhanced by incorporating larger and more diverse datasets as well as patient-specific clinical information. Integrating additional medical data and advanced deep learning techniques may improve the accuracy of brain tumor detection and support more reliable clinical decision-making.

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