



REVIEW ON BRAIN TUMOR DETECTION USING MACHINE LEARNING

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Abstract—Early detection of brain tumors is very important for effective treatment. Traditional methods like biopsy are invasive and risky. This study explores the use of artificial intelligence to automatically detect and classify brain tumors from MRI images. Two deep learning models—a new 2D Convolutional Neural Network (2D-CNN) and an autoencoder-based model—were developed and compared with six traditional machine learning methods. The models classified MRI images into four categories: glioma, meningioma, pituitary tumor, and healthy brain. A dataset of 3,264 MRI images was used, along with image preprocessing and data augmentation. The proposed 2D-CNN achieved the best performance, with high accuracy, recall, and excellent ROC-AUC values close to 1.0. Among traditional methods, KNN performed best, while MLP showed poor results. Statistical analysis showed that deep learning models performed significantly better than traditional methods. Overall, the proposed 2D-CNN is accurate, simple, and fast, making it suitable for clinical use in early brain tumor diagnosis.

Keywords—Brain tumor detection, Magnetic resonance imaging (MRI), Deep learning, Convolutional neural network (CNN), Autoencoder, Machine learning, Medical image classification, Computer-aided diagnosis:

I. INTRODUCTION

Brain tumors are among the most severe neurological disorders, characterized by abnormal tissue growth that disrupts normal brain function and can be fatal if left untreated [3]. Reports from the National Brain Tumor Foundation indicate a significant increase in brain tumor-related mortality over the past three decades, highlighting the critical importance of early diagnosis and treatment [2][4]. However, definitive

diagnosis through biopsy requires invasive neurosurgical procedures, motivating the need for accurate, non-invasive diagnostic alternatives. Magnetic Resonance Imaging (MRI) is currently the most widely used modality for brain tumor detection due to its high spatial resolution and superior soft-tissue contrast [5].

Recent advances in machine learning, particularly deep learning, have enabled automated analysis of medical images through effective feature extraction and pattern recognition. Convolutional Neural Networks (CNNs) and autoencoders have demonstrated strong performance in medical image classification and representation learning tasks, achieving high diagnostic accuracy across various applications [6]. Several studies have applied these techniques to brain tumor classification; however, many existing approaches suffer from limitations such as high computational complexity, lack of comparison with conventional machine learning methods, and exclusion of healthy brain images, which reduces clinical applicability [6].

Moreover, brain tumor diagnosis based solely on medical imaging is highly dependent on radiologist expertise and subject to inter-observer variability. Computer-aided diagnosis systems based on computational intelligence can provide objective and consistent support for clinicians [6]. In this study, we address existing limitations by proposing and systematically comparing eight models, including deep learning and traditional machine learning approaches, to identify an efficient and accurate framework for multi-class brain tumor classification suitable for clinical deployment.

II. LITERATURE REVIEW

A. Brain tumor

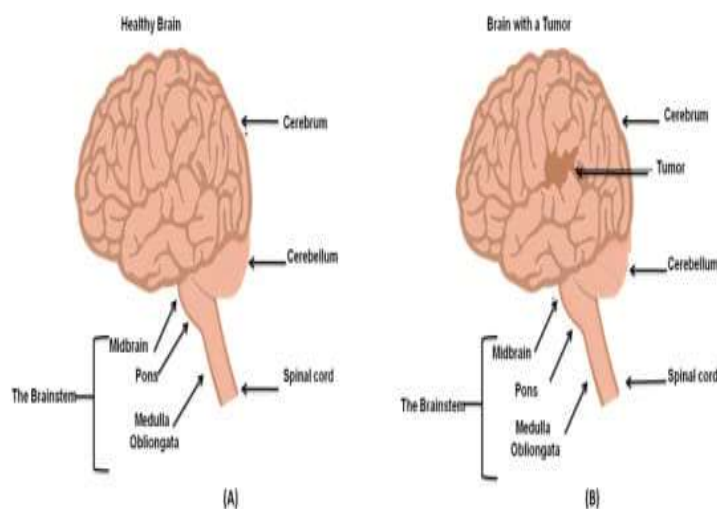


Fig 1[Brain tumor]

Brain tumors represent one of the most serious neurological disorders due to their impact on vital brain functions. They are caused by the uncontrolled growth of abnormal cells within the brain or surrounding tissues. Brain tumors are broadly classified into benign and malignant types, with malignant tumors being more aggressive and life-threatening. Common primary brain tumors include glioma, meningioma, and pituitary tumors, each differing in origin, growth pattern, and clinical behavior. The symptoms of brain tumors vary depending on their size, location, and progression, and may include persistent headaches, seizures, cognitive impairment, vision disturbances, motor weakness, and personality changes. [5]Early



and accurate diagnosis of brain tumors is crucial for improving patient survival rates and treatment outcomes. Magnetic Resonance Imaging (MRI) is the most widely used imaging modality for brain tumor diagnosis due to its high spatial resolution and ability to provide detailed information about soft tissues. However, manual interpretation of MRI scans is time-consuming and highly dependent on the expertise of radiologists, which may lead to variability in diagnosis. Additionally, invasive diagnostic methods such as biopsy pose significant risks and are not always feasible. Recent advances in machine learning and deep learning have shown great potential in automated brain tumor detection and classification. These computational intelligence techniques can learn complex patterns from medical images and assist clinicians by providing fast and accurate diagnostic support. In particular, Convolutional Neural Networks (CNNs) and autoencoder-based models have demonstrated superior performance in feature extraction and image classification tasks. Integrating such intelligent systems into clinical workflows can reduce diagnostic errors, minimize human workload, and support early intervention, ultimately improving patient prognosis. [5][9]

B. RESEARCH ON BRAIN TUMOR

1.Implementation

The implementation of the brain tumor detection system is done using MRI images and computer-based techniques. The main purpose of this system is to help in identifying the presence of a brain tumor in an accurate and simple manner. The entire process is carried out step by step, starting from image collection to final result evaluation. [2]

1. Data Collection:

MRI images of the brain are collected from a publicly available dataset. These images include both normal brain scans and scans that contain tumors. Each image is properly labeled so that the system can learn the difference between healthy and unhealthy brain images. The dataset is divided into two parts: one part is used for training the system and the other part is used for testing its performance.

2. Image Preprocessing:

Before using the images for detection, preprocessing is performed to improve image quality. All MRI images are resized to the same size so that they can be processed uniformly. Unwanted noise present in the images is removed to avoid errors. The pixel values are normalized to make important features clearer. This step helps the system work faster and produce more accurate results.

3. Image Enhancement:

Image enhancement techniques are applied to improve contrast and highlight important regions in the MRI images. This makes the tumor area more visible compared to the surrounding brain tissues. Enhancement helps the system focus on important details and improves detection accuracy.

4. Feature Extraction:

Feature extraction is an important step in tumor detection. Features such as shape, texture, and intensity differences are taken from the MRI images. When using deep learning, these features are automatically learned by the system through multiple layers. This reduces human effort and improves the reliability of the detection process.

5. Model Design:

A Convolutional Neural Network (CNN) is designed for detecting brain tumors. The CNN consists of convolution layers that extract important image patterns, pooling layers that reduce image size and computation, and fully connected layers that perform final classification. Activation functions are used to improve learning efficiency.

6. Model Training:

The CNN model is trained using the training dataset. During training, the system learns from the MRI images by comparing predicted results with actual labels. Errors are reduced by adjusting the model parameters. Training continues until the system achieves acceptable accuracy.

7. Model Testing:

After training, the model is tested using unseen MRI images. This step checks how well the system performs on new data. Testing helps in understanding the reliability and real-world usefulness of the system.

8. Performance Evaluation:

The performance of the system is evaluated using different metrics such as accuracy, precision, recall, and F1-score. A confusion matrix is also used to show correct and incorrect predictions. These results help in analyzing the effectiveness of the proposed system.

9. Tools and Software Used:

The system is implemented using the Python programming language. Libraries such as TensorFlow or Keras are used to build the CNN model. OpenCV is used for image processing tasks, and NumPy is used for numerical calculations. The system is executed on a standard computer with sufficient processing power. [7][3]

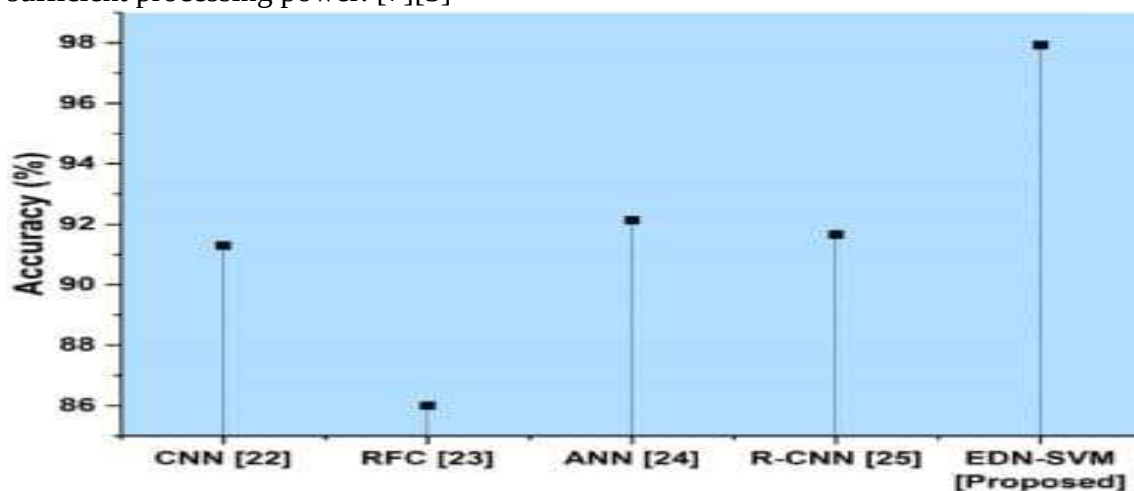


Fig2: [Implementation]

Related works :



The application of machine learning (ML) techniques for brain tumor detection and classification using magnetic resonance imaging (MRI) has gained significant attention in recent years. These methods aim to support radiologists by improving diagnostic accuracy, reducing human error, and enabling early tumor detection. Initial studies focused on traditional machine learning approaches that relied on handcrafted feature extraction methods such as texture analysis, intensity-based features, and statistical descriptors. Classifiers including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Trees (DT), Random Forest (RF), and Multilayer Perceptron (MLP) were commonly used. While these approaches achieved acceptable performance, they required careful feature selection and were sensitive to noise and image quality. With the rapid development of deep learning, Convolutional Neural Networks (CNNs) have become the dominant models for brain tumor classification. CNNs automatically learn discriminative features from MRI images, eliminating the need for manual feature extraction. Several studies have proposed 2D-CNN and 3D-CNN architectures to classify common brain tumor types such as glioma, meningioma, and pituitary tumors. Transfer learning approaches using pretrained models such as VGGNet, AlexNet, ResNet, and DenseNet have also been widely explored to improve classification accuracy, especially when training data is limited. Despite their strong performance, these deep learning models often require high computational power and large datasets, which may limit their use in real-time clinical systems. Capsule Networks have been introduced as an alternative to CNNs to better preserve spatial relationships between image features. Models such as DCNet and DCNet++ demonstrated improved feature learning capabilities for complex MRI data; however, their increased architectural complexity and training cost remain significant challenges. Autoencoder-based models, particularly convolutional autoencoders, have also been applied for unsupervised feature extraction and dimensionality reduction in brain tumor analysis. These models can capture meaningful latent representations, which are then used by classifiers for tumor identification, but they add additional processing stages to the overall system. Hybrid approaches combining deep learning feature extractors with traditional machine learning classifiers have also been proposed. In such frameworks, CNNs or autoencoders are used to extract high-level features, which are then classified using SVM, KNN, or other ML algorithms. While these hybrid models often achieve improved performance, many studies focus solely on tumor classification and exclude healthy brain images, limiting their effectiveness in practical screening scenarios. Although significant progress has been made, several challenges remain in existing research. Many studies lack comprehensive comparative evaluations between deep learning and traditional machine learning methods. Additionally, issues such as class imbalance, limited dataset diversity, high computational complexity, and lack of explainability reduce the clinical acceptance of these systems. These limitations highlight the need for efficient, accurate, and interpretable machine learning models that can classify multiple brain tumor types and healthy cases while being suitable for real-world clinical deployment. [1][4]

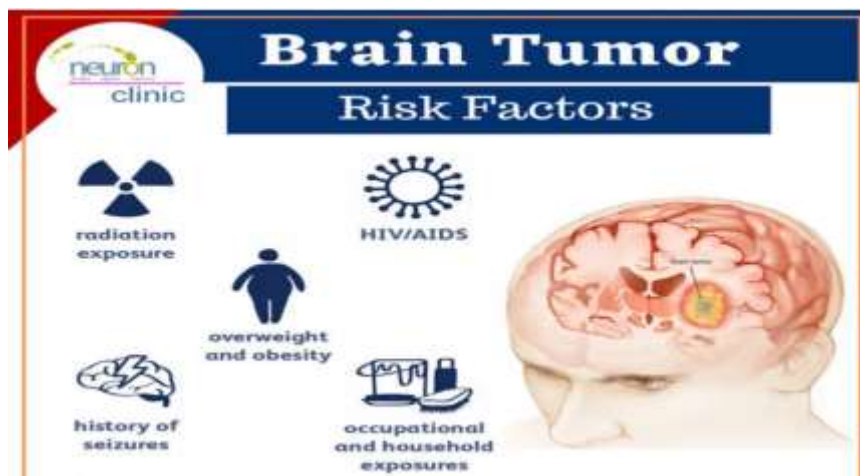


Fig 3[Risk factors]

➤ **PROBLEM STATEMENTS**

Brain tumors can cause serious health problems that affect both the body and brain, often leading to pain and long-term treatment. The impact of a brain tumor depends on its size, type, and location in the brain. In some cases, tumors press on areas that control movement, causing physical disability. If the tumor is detected late, the damage can become permanent. Early detection is therefore very important to reduce complications. However, identifying brain tumors at an early stage is difficult. Brain tumors vary widely in shape, size, and intensity in MRI images. Different tumor types can also look very similar in scans. This makes accurate classification challenging. Hence, reliable automated methods are needed for early and correct brain tumor detection. [2][7]

➤ **Dataset Collection**

The dataset used in this study was collected from the publicly available Kaggle open-access repository and was utilized to evaluate the effectiveness of the proposed brain tumor classification model. The dataset comprises a total of 255 T1-weighted magnetic resonance imaging (MRI) brain scans, of which 98 images correspond to healthy subjects and 155 images represent brains affected by tumors. T1-weighted MRI images are widely used in clinical practice due to their ability to provide clear anatomical details, making them suitable for tumor detection and analysis. One of the main challenges associated with this dataset is the variation in image resolution, size, and orientation, which arises due to differences in MRI acquisition protocols and imaging equipment. Such inconsistencies can significantly affect the performance of machine learning and deep learning models, as these models require input data of uniform dimensions. To address this challenge, all MRI images were resized to a fixed spatial resolution with consistent width and height. This resizing process ensures uniformity across the dataset, enabling efficient batch processing and stable model training while also reducing computational complexity.[8] After resizing, the dataset becomes well-suited for additional preprocessing operations. These include noise reduction to remove unwanted artifacts, intensity normalization to standardize pixel value distributions, and data augmentation techniques such as rotation, flipping, and scaling to increase data diversity. These preprocessing steps play a crucial role in enhancing the robustness of the model by improving feature learning and reducing overfitting. As a result, the prepared dataset supports improved

model generalization and contributes to higher classification accuracy and more reliable performance in brain tumor detection tasks show an effect.[5,8]

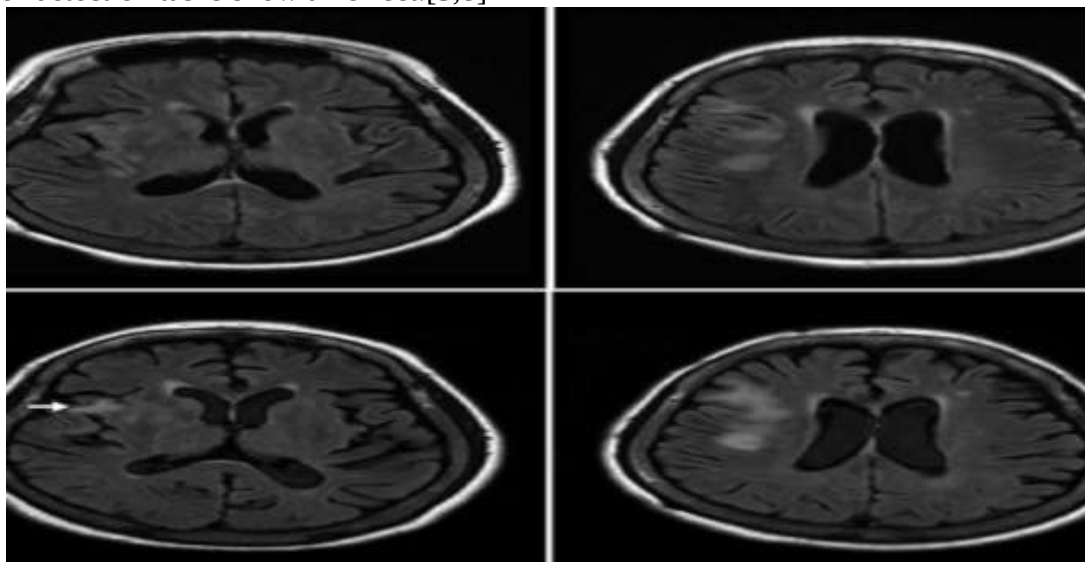


Fig :4[dataset system]

➤ **PREPROCESSING :**

Preprocessing is an essential stage in MRI brain tumor analysis, as it directly affects the accuracy and reliability of the classification system. Raw MRI images often differ in size, brightness, and quality due to variations in scanning equipment and acquisition conditions. To address this, the first preprocessing step involves resizing all images to a fixed dimension. This creates uniformity across the dataset and allows the model to learn patterns effectively without being influenced by image size differences. Once the images are resized, contrast enhancement is performed to improve the distinction between healthy brain tissue and tumor regions. Tumors may appear faint or blend with surrounding tissues, so enhancing contrast makes these regions clearer and easier to detect. Noise reduction techniques are then applied to remove unwanted distortions such as speckle noise or random pixel variations. This step improves image clarity while preserving important structural details of the brain. Following noise removal, normalization is applied to scale pixel intensity values into a consistent range. This helps reduce variations in brightness and improves the learning efficiency of machine learning and deep learning models. In some cases, filtering or smoothing operations are also used to refine image edges and reduce irregularities. Overall, preprocessing ensures that the MRI images are clean, consistent, and informative, which significantly improves feature extraction and leads to more accurate brain tumor classification.[9]

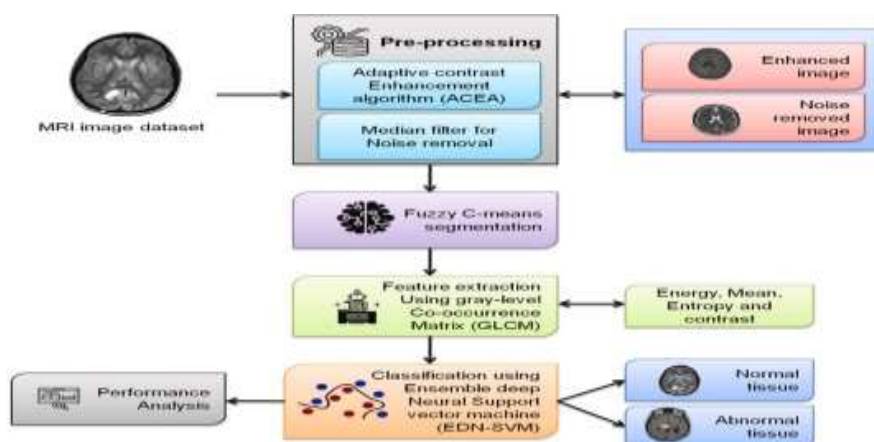


Fig 5: [Pre-processing]

➤ Types of brain tumor

A brain tumor is an abnormal growth of cells inside the brain or near the brain. Brain tumors can affect the normal working of the brain by pressing on important areas. Based on their nature and origin, brain tumors are classified into different types. Understanding these types helps in early detection and proper treatment. [6][1][8]

1. Benign Brain Tumors:

Benign brain tumors are non-cancerous tumors. They grow slowly and usually do not spread to other parts of the brain or body. These tumors often have clear boundaries and can sometimes be removed through surgery. Even though they are not cancerous, benign tumors can still cause problems such as headaches, vision issues, and seizures if they press on important brain areas. Early detection helps in reducing complications.

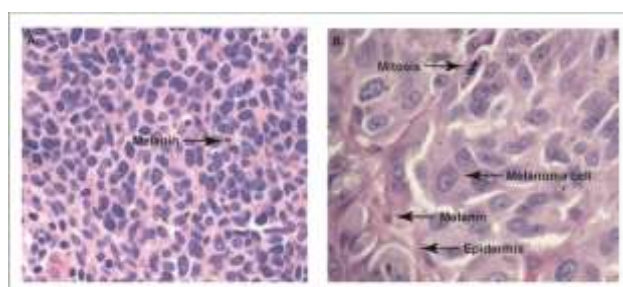


Fig 6: [Benign Brain Tumors]

2. Malignant Brain Tumors:

Malignant brain tumors are cancerous and dangerous in nature. They grow very fast and can spread into nearby brain tissues. These tumors are more difficult to treat and may return even after treatment. Malignant tumors often require advanced treatments such as surgery, radiation therapy, and chemotherapy. Early detection plays a very important role in improving patient survival.

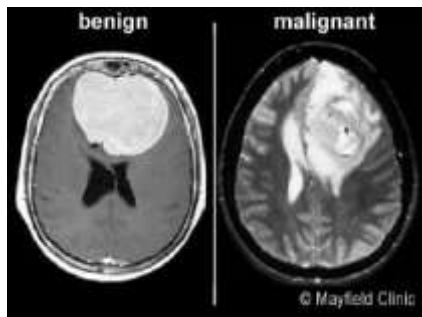


Fig 7: [Malignant Brain Tumors]

3. Gliomas:

Gliomas are one of the most common types of brain tumors. They develop from glial cells, which support and protect nerve cells in the brain. Gliomas can be either benign or malignant. Common types of gliomas include astrocytomas, oligodendrogliomas, and glioblastomas. These tumors usually grow inside the brain tissue, making them difficult to remove completely. Accurate detection is essential for effective treatment planning.



Fig 8: [Gliomas]

4. Meningiomas:

Meningiomas grow from the meninges, which are the protective layers covering the brain and spinal cord. Most meningiomas are benign and grow slowly. In many cases, they do not cause symptoms for a long time and are detected during routine brain scans. However, if they grow large, they may press on the brain and cause neurological problems. Regular monitoring is important for managing these tumors.

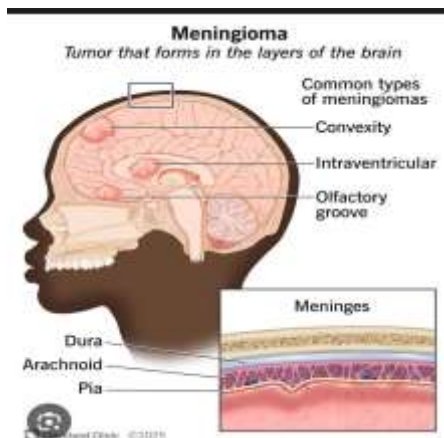


Fig 9: [Meningiomas]

5. Pituitary Tumors:

Pituitary tumors develop in the pituitary gland, which controls hormone production in the body. These tumors are usually benign but can affect hormone levels, leading to health problems such as weight changes, vision loss, and fatigue. MRI scans are commonly used to detect pituitary tumors due to their location and size.

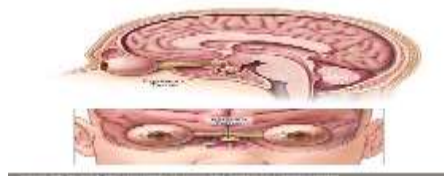


Fig 10: [Pituitary Tumors]

6. Metastatic Brain Tumors:

Metastatic brain tumors occur when cancer from other parts of the body spreads to the brain. Common primary cancer sources include the lungs, breast, and kidneys. These tumors are always malignant and often appear as multiple tumors in the brain. Early detection helps doctors choose suitable treatment methods and improve the patient's quality of life.[5]

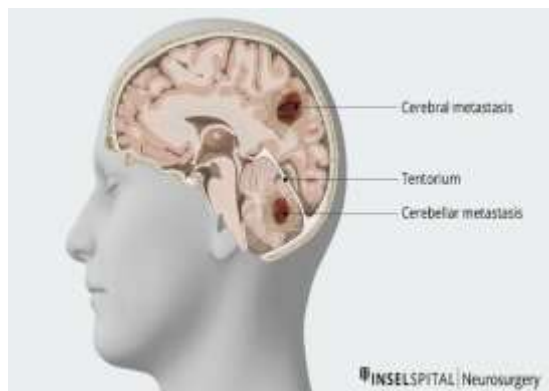


Fig 11: [Metastatic Brain Tumors]

ALGORITHMS:

Convolutional Neural Network (CNN):

A Convolutional Neural Network (CNN) is a deep learning algorithm mainly used for image-based applications. In brain tumor detection, CNN works directly on MRI images and learns important features automatically. It does not require manual feature extraction. The convolution layers identify patterns such as edges, shapes, and tumor regions in the images. Pooling layers reduce the image size and help the model work faster. Fully connected layers classify the image as normal or tumor-affected. CNN provides high accuracy and is widely used in medical image analysis.[9]

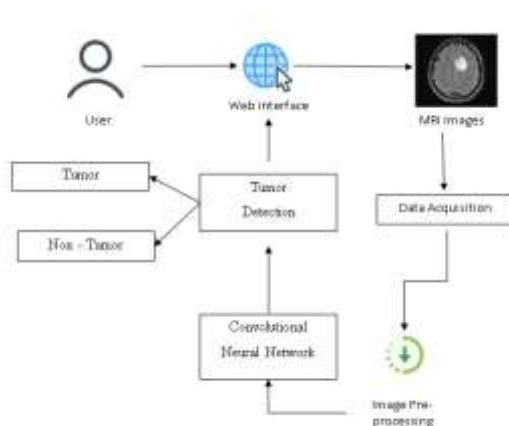


Fig 12: [CNN - Networks]

Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification problems. In brain tumor detection, SVM separates MRI images into different classes based on extracted features. It works by finding a boundary that best divides tumor and non-tumor images. SVM is effective

when the dataset size is small and provides reliable results. It is commonly used with image processing techniques to improve detection accuracy.

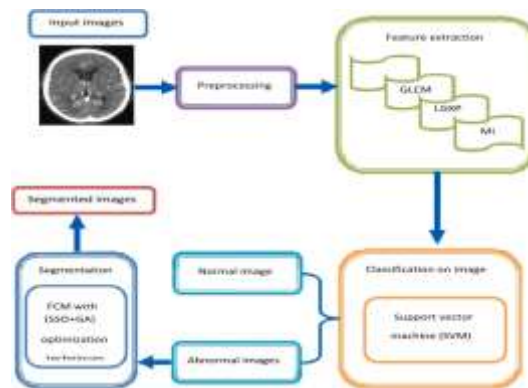


Fig 13: [SVM - Networks]

K-Nearest Neighbors (KNN):

K-Nearest Neighbors (KNN) is a simple classification algorithm that works based on similarity. It compares a new MRI image with existing images in the dataset and finds the closest matches. The image is classified based on the majority category of its nearest neighbors. KNN is easy to implement and understand. However, it may require more computation time when the dataset becomes large.

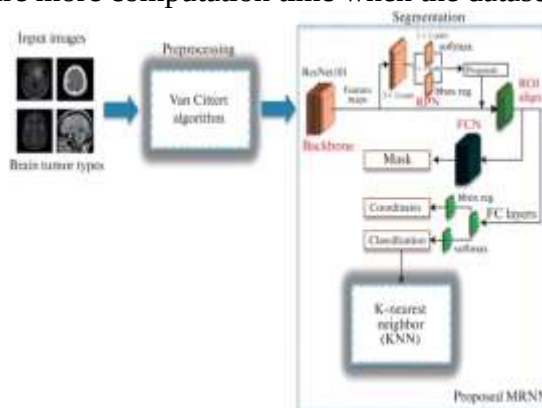


Fig 14: [KNN - Networks]

Transfer Learning:

Transfer learning is a deep learning approach that uses already trained models for new tasks. Popular models like VGG16, ResNet, and Inception are trained on large image datasets and reused for brain tumor detection. Transfer learning helps achieve good results even when the MRI dataset is limited. It reduces training time and improves performance by using previously learned feat.



Fig 15: [TL - Networks]

Future Scope:

The proposed brain tumor detection system shows promising results, but there are several ways in which it can be further improved in the future. Larger and more diverse MRI datasets can be used to train the system, which will help improve accuracy and reliability for real patient data. Advanced deep learning models such as transfer learning and hybrid techniques can be explored to improve performance and reduce training time. These methods may help in detecting brain tumors at earlier stages with better accuracy. The system can be extended to detect not only the presence of a tumor but also its exact location and size. By adding tumor segmentation techniques, the affected region can be clearly highlighted in MRI images, which will support doctors in diagnosis and treatment planning. In the future, the system can be integrated into web or mobile applications to support remote diagnosis and telemedicine. With further testing and clinical validation, this system can become a useful decision-support tool for medical professionals. [8][5]

CONCLUSION:

In this research paper, a brain tumor detection system using MRI images and machine learning techniques has been presented. The proposed system focuses on identifying the presence of brain tumors in an accurate and efficient manner. Image preprocessing and deep learning methods help improve the quality of images and support better tumor detection.

The use of a Convolutional Neural Network (CNN) allows the system to automatically learn important features from MRI images without manual effort. The experimental results show that the system performs well in distinguishing between normal and tumor-affected brain images. Performance evaluation using accuracy and other metrics confirms the effectiveness of the proposed approach. Overall, the developed system demonstrates that machine learning can play an important role in medical image analysis and assist doctors in early diagnosis. With further improvements and real-world testing, the proposed method can be used as a supportive tool in healthcare applications for brain tumor detection.[3]

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