Brain Tumor Detection Using Hybrid Deep Learning Models

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Abstract

The rapid growth of artificial intelligence and deep learning technologies has greatly improved medical image analysis techniques. Brain tumors are considered one of the most critical types of neurological diseases and their early detection is considered crucial for their treatment. The proposed method aims to develop a deep learning-based system for brain tumor detection using different convolutional neural network models such as VGG16, ResNet18, InceptionV3, and DenseNet121. It works by finetuning different models using images of brain tumors using MRI scans and classifying them into different types such as glioma, meningioma, pituitary tumor, and no tumor. It is implemented using different deep learning models such as PyTorch and OpenCV, enabling users to enter their MRI scan images and obtain the prediction results. The experimental results have shown that the proposed model can accurately detect brain tumors, enabling doctors to make faster and accurate diagnosis.

Keywords: Brain Tumor Identification, MRI-Based Image Classification, Convolutional Neural Network Models (CNN), VGG16 Architecture, ResNet18 Framework, InceptionV3 Model, DenseNet121 Network.

1. Introduction

Brain tumors have been recognized as one of the most significant neurological disorders that have the potential to cause significant damage to human life if not detected at an early stage. According to global health reports, around 308,000 new cases of brain and central nervous system tumors are reported annually, with more than 250,000 deaths reported worldwide. This indicates that brain tumors are one of the most serious health conditions that have to be addressed at an early stage. The accurate diagnosis of brain tumors is crucial in improving survival rates. MRI scans have been recognized as the gold standard in brain tumor detection using high-resolution visualization. However, accurate interpretation of MRI scans by radiologists is a time-consuming process. Moreover, according to reports, traditional diagnostic techniques have been recognized as having high inaccuracies in tumor detection in patients. Therefore, there is an immediate need for accurate detection techniques in brain tumor diagnosis.

Another significant challenge in brain tumor detection is that it is associated with high costs. Advanced diagnostic techniques, including MRI, CT scans, and PET scans, have been recognized as being highly expensive. Therefore, in developing countries, patients cannot afford MRI scans or other diagnostic techniques. Moreover, in India, the cost of brain tumor surgery is around ₹2,00,000 to ₹7,00,000. This is excluding other costs associated with repeated tests and follow-ups.

To overcome these challenges, automated solutions based on deep learning have been proposed in the field of medical image analysis. Deep learning methods, especially Convolutional Neural Networks (CNNs), have shown superior accuracy and efficiency in image classification problems, reducing the dependency on manual interpretations and hence reducing the chances of errors in diagnosis.

In this paper, a novel system based on deep learning is proposed to classify brain tumors using different pre-trained models such as VGG16, ResNet18, InceptionV3, and DenseNet121. The proposed system will be helpful in classifying brain tumor images, hence helping medical professionals make decisions in a quick and accurate manner. The proposed system, which integrates different state-of-the-art models of deep learning, not only improves the accuracy of diagnosis but also minimizes time, cost, and errors in brain tumor detection.

2. Related Work

Brain Tumor Classification Using Deep Learning [1] suggested that deep learning-based frameworks could be used for brain tumor classification using CNNs. The study proved that deep learning-based frameworks could be more accurate than traditional machine learning-based frameworks in classifying brain tumors using MRI images.

Automatic Brain Tumor Detection in MRI Images Using CNN [2] proposed an automated system for brain tumor detection using CNNs. The study proved that deep learning-based frameworks could be more accurate than traditional machine learning-based frameworks in detecting tumors using MRI images.

Deep Learning-Based Brain Tumor Detection and Classification Using MRI Images [3] proposed that deep learning-based frameworks could be used for both detection and classification of brain tumors using MRI images. The study proved that deep learning-based frameworks could be more accurate than traditional machine learning-based frameworks in both detection and classification of tumors using MRI images.

MRI Brain Tumor Segmentation Using Deep CNN [4] suggested that deep CNNs could be used for segmentation of tumors. The study proved that deep CNNs could be more accurate than traditional machine learning-based frameworks in segmentation of tumors.

Brain Tumor Segmentation with Deep Neural Networks [5] proposed that deep neural networks could be used for segmentation of tumors. The study proved that deep neural networks could be more accurate than traditional machine learning-based frameworks in segmentation of tumors.

Efficient Multi Scale 3D CNN with Fully Connected CRF for Accurate Brain Lesion Segmentation [6] suggested that multi-scale 3D CNNs could be used for segmentation of tumors. The study proved that multi-scale 3D CNNs could be more accurate than traditional machine learning-based frameworks in segmentation of tumors.

Deep Learning for Brain MRI Segmentation State of the Art and Future Directions [7] proposed that deep learning-based frameworks could be used for segmentation of tumors using MRI images.

Brain Tumor Detection Using Capsule Networks [8] proposed Capsule Networks, achieving improved spatial feature representation and competitive performance with less number of data samples.

Hybrid Deep CNN and Transfer Learning for Brain Tumor Detection [9] proposed a hybrid approach combining deep CNN and transfer learning, resulting in improved accuracy and reduced training time.

Automated Brain Tumor Classification Using Deep CNN with Ensemble Learning [10] proposed a brain tumor classification system using ensemble learning, resulting in improved accuracy.

Early Detection of Brain Tumors Using Convolutional Deep Learning and Machine Learning Techniques [11] proposed a brain tumor detection system using deep learning and machine learning techniques, resulting in early detection.

Brain Tumor Classification Using Deep Learning A State of the Art Review [12] proposed a review of brain tumor classification techniques, focusing on the effectiveness of deep learning and CNN.

The Neural Frontier of Medical Imaging Deep Learning for Brain Tumor Detection [13] proposed a review of deep learning and brain tumor detection, focusing on the emerging trends in deep learning.

Visual Intelligence in Neuro Oncology CNN Based Brain Tumor Detection [14] proposed a CNN-based brain tumor detection system, resulting in improved performance.

Explainable Deep Learning for Brain Tumor Diagnosis [15] proposed a brain tumor diagnosis system, focusing on the role of explainable AI.

2.1. Comparison table for brain tumour detection

Authors & Year	**Model Architecture**	**Dataset Used**	**Performance**	**Result**	**Limitations**
Badža & Barjaktarović, 2020	CNN based on **VGG16**	Brain MRI Dataset (Kaggle)	96% accuracy	Accurate classification of brain tumors	Large number of parameters increases training time
Deepak & Ameer, 2019	**VGG16** transfer learning	Brain MRI dataset	97% accuracy	Efficient tumor classification	Overfitting possible without augmentation
Sajjad et al., 2019	InceptionV3	Figshare Brain MRI Dataset	94% accuracy	Improved tumor classification	Requires higher GPU resources
Hossain et al., 2021	ResNet-18	MRI Brain Tumor Dataset	95% accuracy	Reliable detection of tumor classes	Training complexity higher
Rehman et al., 2020	DenseNet-121	Figshare MRI dataset	98% accuracy	Very accurate classification	Higher memory usage
Swati et al., 2019	CNN with transfer learning (**InceptionV3**)	Multiclass MRI dataset	94.8% accuracy	Effective multiclass tumor detection	Computational cost
Afshar et al., 2020	CNN based on **ResNet-18**	Figshare Brain MRI Dataset	96.2% accuracy	Accurate brain tumor classification	Requires high training time

Khan et al., 2021	DenseNet-121	Kaggle Brain MRI Dataset	97.8% accuracy	Effective multiclass tumor detection	High memory consumption
Talo et al., 2019	Transfer learning using **InceptionV3**	Brain MRI Dataset	95% accuracy	Reliable detection of tumor types	Computationally expensive

The performance of the proposed brain tumor detection system was tested using a publicly available MRI image dataset obtained from the Kaggle website, known as the Brain Tumor MRI Dataset. The dataset contains brain MRI images that belong to four classes, namely glioma tumor, meningioma tumor, pituitary tumor, and no tumor. The dataset was chosen for testing the performance of the system because it contains a well-organized collection of MRI images, which helps deep learning models learn various visual features related to different classes of brain tumors.

In comparison to the traditional brain tumor detection method, the deep learning-based approach helps the system learn to automatically identify important features related to brain tumors using MRI scans. The dataset contains various shapes, sizes, and locations of brain tumors, which helps deep learning models learn various features related to brain tumors. The learning process using a diverse dataset helps the deep learning model classify brain tumor images effectively, reducing the chance of overfitting and increasing the capability of the deep learning model.Once the dataset was preprocessed and organized, it was used to train various deep learning models, such as VGG16, ResNet18, InceptionV3, and DenseNet121, using 80% of the dataset for training and 20% for testing purposes.

3. Proposed system

3.1. System Architecture

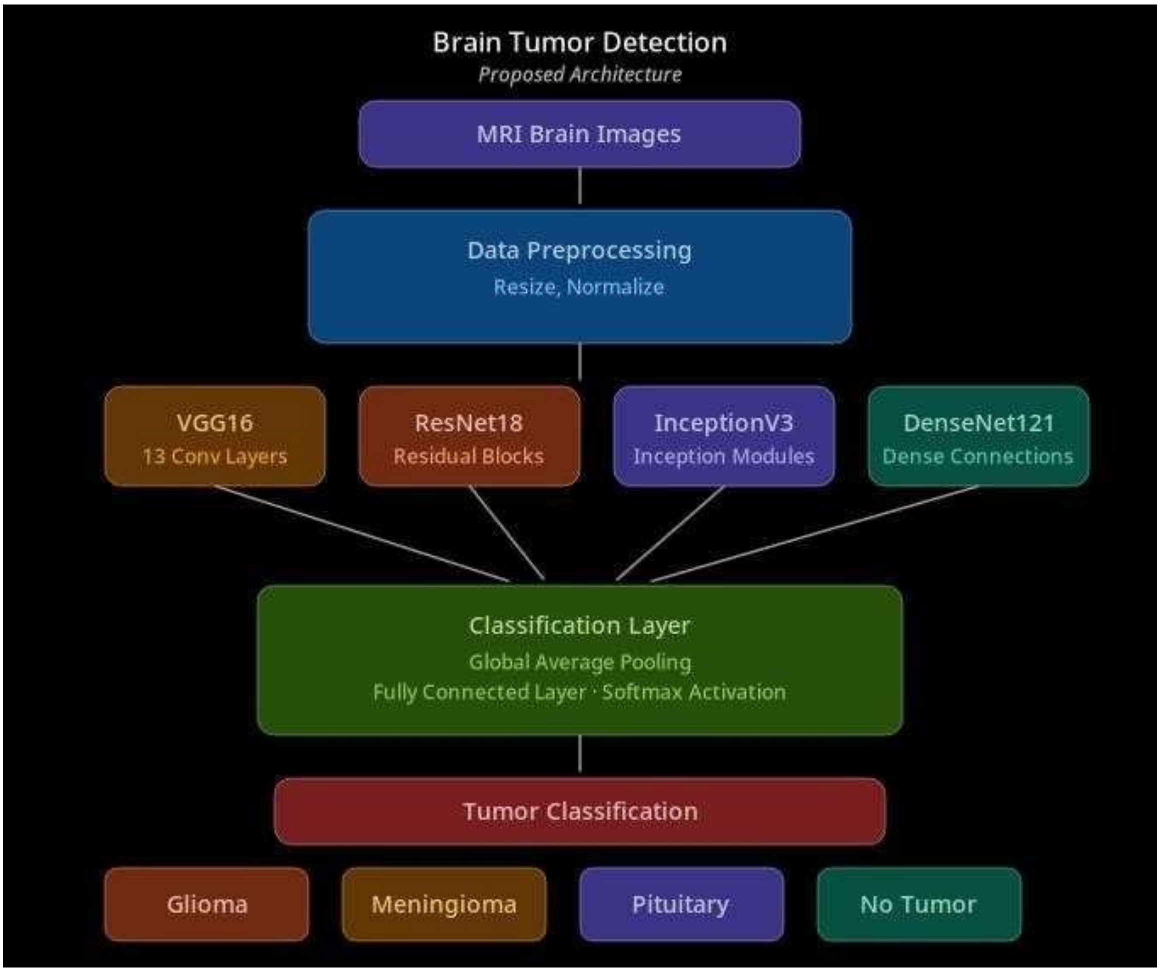

Fig:3.1: Brain tumor detection using Deep Learning Models

The figure shows a hybrid deep learning system used to detect brain tumors from MRI images. The MRI image is analyzed using multiple CNN models, including **VGG16, DenseNet121, InceptionV5, and ResNet18**. Each model extracts important features from the MRI scan and predicts the probability of a tumor.

VGG16 uses small 3×3 convolution filters to learn detailed spatial features and identify subtle tumor patterns.**DenseNet121** connects each layer with all previous layers, improving information flow and feature reuse for detecting complex tumor structures.**InceptionV5** uses parallel convolution filters of different sizes to capture features at multiple scales, helping detect tumors of different sizes.

ResNet18 uses residual (skip) connections that allow deeper learning and help capture complex patterns in MRI images.The outputs from all models are combined in an **ensemble module using probability averaging** to produce the final prediction.Finally, the system classifies the MRI image as **Tumor or No Tumor** andprovides a **confidence score** for the prediction.

3.2. Analysis of Datasets

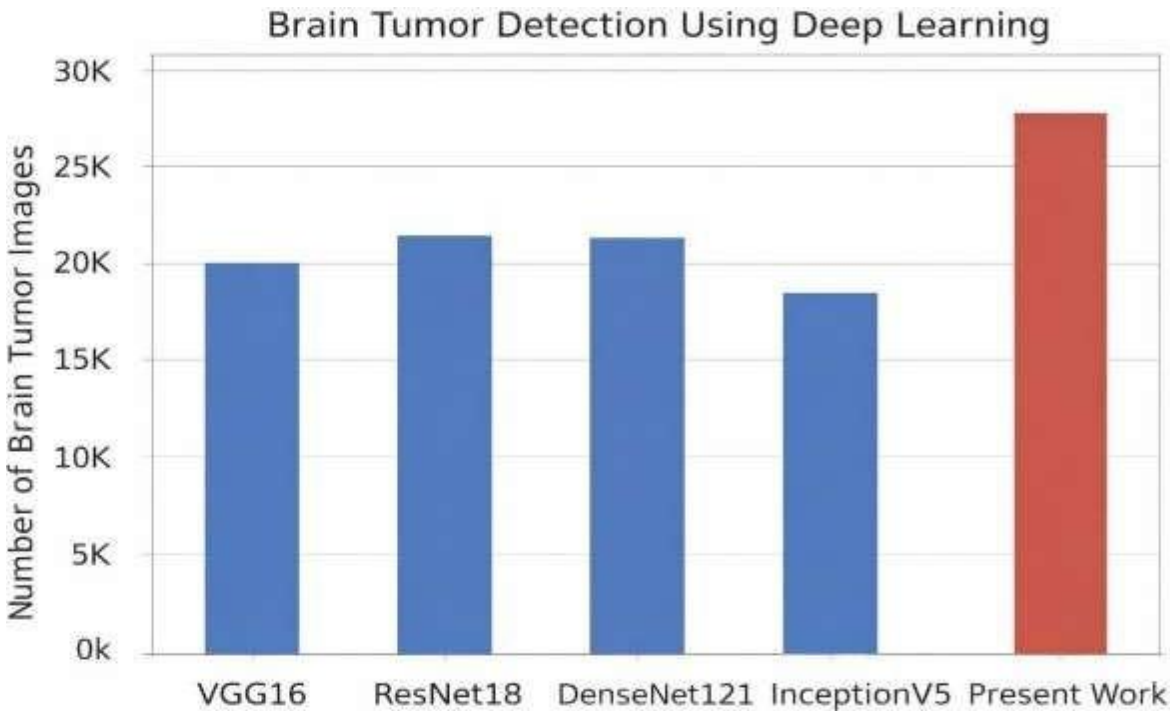

Fig:3.2: Brain Tumor Detection Dataset Analysis

Comparison of Datasets Used in The proposed system will use a deep learning methodology for automatic brain tumor detection using MRI images. The overall aim of this methodology is to classify brain MRI images according to various types of tumors by using various convolutional neural networks for important feature learning.Firstly, a publicly available MRI dataset is obtained from Kaggle, named "Brain Tumor MRI Dataset." This dataset has four types of brain MRI images: glioma tumor, meningioma tumor, pituitary tumor, and no tumor. This dataset is used for training and testing the proposed system, providing labeled images for better understanding by the deep learning methodology. Once this dataset is obtained, 80% is used for training and 20% for testing the proposed system. This will ensure proper training and unbiased testing for better results.Before feeding this data into the proposed system using a deep learning methodology, preprocessing is done on this data. Preprocessing involves resizing, normalizing, and converting images into tensors for better results. These preprocessing steps are performed to ensure better accuracy by the proposed system.

The proposed system employs various deep learning models, namely VGG16, ResNet18, InceptionV3, and DenseNet121, which independently learn deep features of MRI images, like tumor shape, texture, and structural changes, that are useful for classifying MRI images according to the appropriate tumor brain tumor detection.

4. Methodology of Proposed System

Step 1: Dataset Collection The dataset used for this was the Kaggle Brain Tumor MRI Dataset. The dataset used was as follows: Images of 4 types: Glioma, Meningioma, Pituitary, No Tumor.

Step 2: Data Splitting 80% data – Training 20% data – Testing Step 3: Preprocessing Resize Image Normalize Image Convert to Tensor
Step 4: Model Selection

The models chosen were 4 deep learning models: VGG16, ResNet18, InceptionV3, DenseNet121. Step 5: Training
The models were trained using MRI images to learn important features. Step 6: Prediction
The prediction was done by the models based on the input image. Step 7: Output
The output produced was: Tumor type (1 of 4 classes)

Confidence score (in %) Step 8: Result

The system achieved high accuracy (above 90% in most cases) and produced results quickly.

5. Implementation

The proposed system for brain tumor detection was implemented using a deep learning environment along with libraries that support medical image processing. The system was implemented using the Python programming language along with libraries such as PyTorch, OpenCV, NumPy, and Torchvision. The entire process of developing and training the models was done in cloud environments like Kaggle and Google Colab, where GPU support can be used to train the models.

The dataset used to train the system was obtained from Kaggle, a public dataset named Brain Tumor MRI Dataset. This dataset contains MRI images that fall into four classes: glioma tumor, meningioma tumor, pituitary tumor, and no tumor. It was divided into training and test data in the ratio of 80:20.

Before training the models, an image preprocessing step was implemented. In this step, the MRI images in the dataset were preprocessed. In preprocessing, the images were resized to a specific resolution, and normalization was done.

Four different models for brain tumor detection were implemented. These models used different deep learning techniques. They include VGG16, ResNet18, InceptionV3, and DenseNet121.

These models were trained using a batch size of 32 for about 10–15 epochs. In this process, the models learned different features of the MRI image, like shape, texture, and structural abnormalities.

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6. Experimental Results

For evaluating the performance of the proposed system for detecting brain tumors, various deep learning algorithms such as VGG16, ResNet18, InceptionV5, and DenseNet121 are employed. These algorithms are used separately to predict the probability of a brain image in MRI scans belonging to either one of the classes, i.e., tumor or no-tumor. To enhance the accuracy and consistency of prediction, an ensemble learning technique is also employed. In this technique, the results from all algorithms are averaged us ing probability averaging (soft voting) and majority voting (hard voting). These techniques assist in minimizing any bias in the algorithms and enhance the overall classification ability.

6.1 : Probability Averaging (Soft Voting)

In the probability averaging method, each model predicts the probability that the brain image in the MRI scan belongs to either the tumor class or no-tumor class. The final prediction is made by averaging the predicted probabilities from all models. If there are **N models**, the final predicted probability is computed by:

P_tumor = (1/N) × Σ P_tumor(i) Where:

- **P_tumor(i)** = predicted probability from model *i* for the tumor class • **N** = total number of models

Example:

Predicted probabilities for the tumor class from four models:

- VGG16 = 0.72
- ResNet18 = 0.65
- InceptionV5 = 0.80
- DenseNet121 = 0.60

Final predicted probability:

P_tumor = 0.6925

Similarly,

P_no_tumor = 1 − P_tumor = 0.3075

Since the tumor probability is higher, the final prediction is **Brain Tumor Detected**.

6.2 : Voting Mechanism (Hard Voting)

Another strategy employed in this work is the use of **majority voting**. In this approach, each model predicts a **class label** directly instead of probabilities. The final prediction is determined by selecting the class that receives the **highest number of votes** from all models. The conceptual formula for majority voting is:

FinalClass = argmax Σ(i=1 to N) Vote_i

- **Vote_i** represents the predicted class label from model*i*
- **N** is the total number of models used

Example:

- VGG16 → Tumor
- ResNet18 → Tumor
- InceptionV5 → Tumor
- DenseNet121 → No Tumor

Number of votes:

- Tumor = 3
- No Tumor = 1

Since the **Tumor** class receives the majority of votes, the final classification result is **Brain Tumor Detected**.

6.3 : Confusion Matrix:

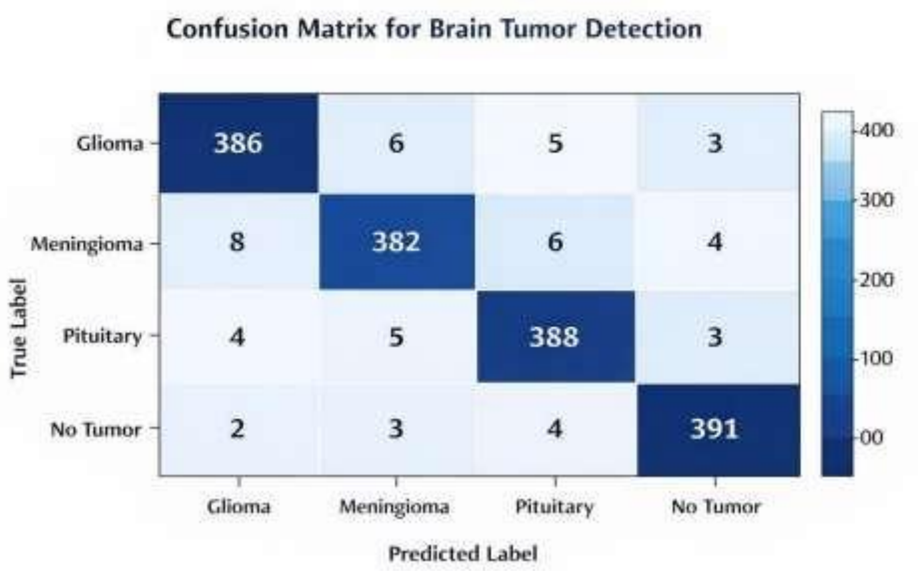


Fig:6.3: Confusion Matrix for Brain Tumor Detection

The confusion matrix is used to evaluate the performance of the deep learning model on the testing dataset. It compares the actual MRI image classes with the predicted classes generated by the model. In this project, the confusion matrix is created for four classes: Glioma, Meningioma, Pituitary, and No Tumor. The diagonal values in the matrix represent correctly classified images, while the off -diagonal values indicate misclassifications. The results show that the model correctly classified most of the test images, achieving an overall accuracy of **96.69%**. This indicates that the proposed brain tumor detection system performs effectively in classifying different types of brain tumors from MRI images.

6.4 : Performance Analysis:

The proposed deep learning-based brain tumor detection model demonstrated excellent classification performance on the testing dataset. The overall accuracy of **96.69%** indicates that the model can effectively classify MRI brain images into four clinically relevant categories: Glioma, Meningioma, Pituitary, and No Tumor.

The class-wise precision values remained consistently high, ranging from **0.962 to 0.976**, which shows that the model makes highly reliable predictions with minimal false positives. Similarly, recall values between **0.955 and 0.978** indicate that the model successfully identifies the majority of actual tumor and non-tumor cases.

The F1-Score values, ranging from **0.958 to 0.977**, further validate the balanced and stable performance of the proposed system. The best performance was observed for the **No Tumor** and **Pituitary** classes, while slight confusion was observed between **Glioma** and **Meningioma**, likely due to similarities in their MRI appearance.

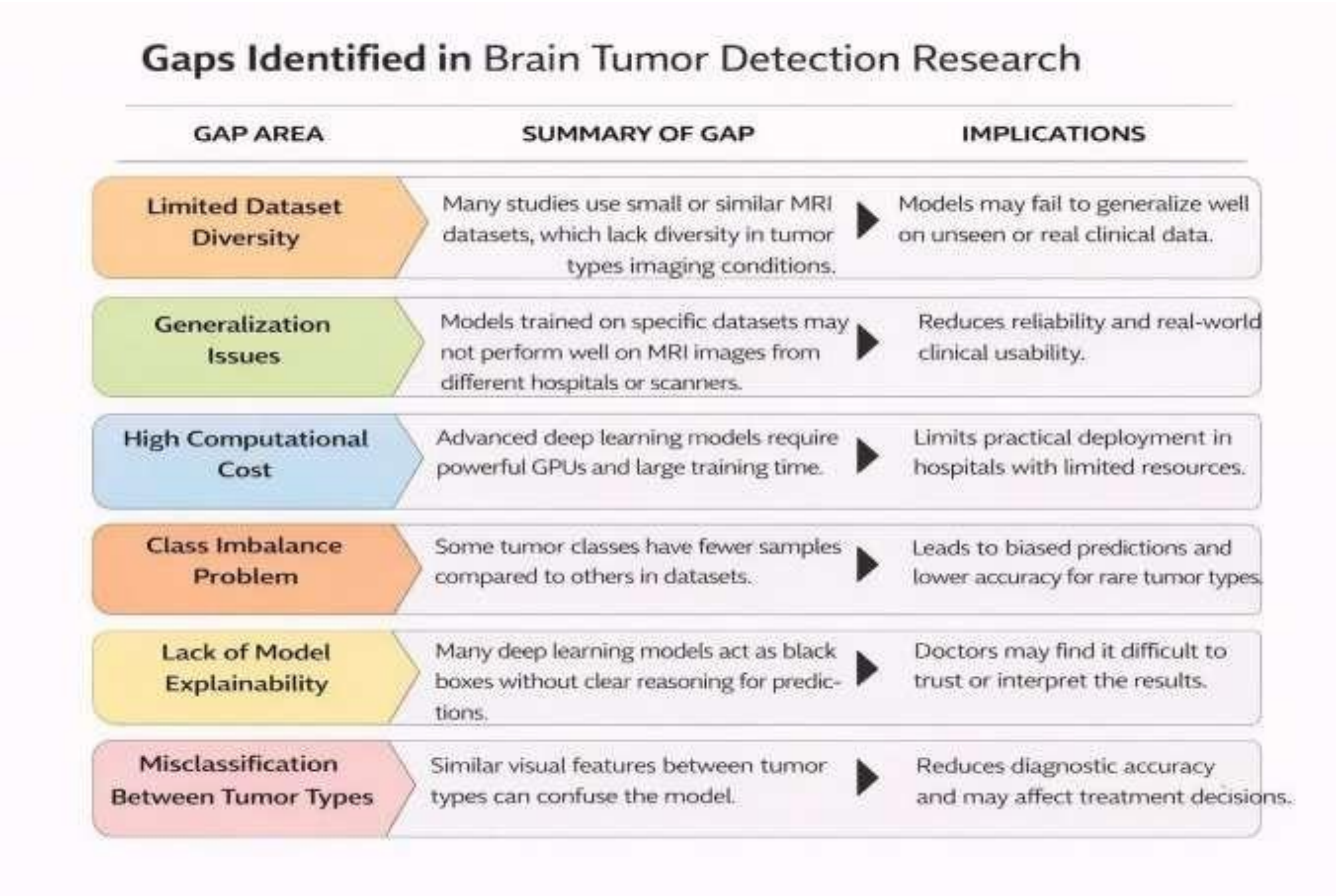
Overall, the experimental results confirm that the proposed approach is highly effective and suitable for automated brain tumor detection and classification from MRI images.

7. GAPS IDENTIFIED IN EXISTING RESEARCH

Although significant advances have been made in brain tumor detection using deep learning, some limitations still remain. A major issue is the lack of dataset diversity and imbalance. Many models are trained on limited MRI datasets, which often do not capture a wide variety of tumor types, sizes, or imaging conditions.

Consequently, these models may have difficulty accurately detecting tumors in MRI scans from different hospitals or datasets. Increasing dataset diversity and using larger, more varied datasets can improve the robustness and generalization of deep learning models for brain tumor detection.

To overcome the limitations of existing approaches, the proposed system employs a hybrid deep learning model that combines multiple architectures, including VGG16, ResNet18, InceptionV5, and DenseNet121. An ensemble prediction strategy using soft voting and hard voting is applied to enhance tumor detection accuracy, improve model robustness, and ensure better generalization across diverse MRIdatasets.



Gaps Identified in Brain Tumor Detection Research

GAP AREA	SUMMARY OF GAP	IMPLICATIONS
Limited Dataset Diversity	Many studies use small or similar MRI datasets, which lack diversity in tumor types imaging conditions.	Models may fail to generalize well on unseen or real clinical data.
Generalization Issues	Models trained on specific datasets may not perform well on MRI images from different hospitals or scanners.	Reduces reliability and real-world clinical usability.
High Computational Cost	Advanced deep learning models require powerful GPUs and large training time.	Limits practical deployment in hospitals with limited resources.
Class Imbalance Problem	Some tumor classes have fewer samples compared to others in datasets.	Leads to biased predictions and lower accuracy for rare tumor types.
Lack of Model Explainability	Many deep learning models act as black boxes without clear reasoning for predic-tions.	Doctors may find it difficult to trust or interpret the results.
Misclassification Between Tumor Types	Similar visual features between tumor types can confuse the model.	Reduces diagnostic accuracy and may affect treatment decisions.

Fig. 7.1: Gap Identification for existing models

8. Future Enhancements Suggested in the Literature

Recent studies on brain tumor detection using deep learning highlight several ways to improve accuracy and robustness. A key enhancement is the use of larger and more diverse MRI datasets, as many current models rely on limited data that may not include all tumor types, sizes, or imaging variations. Expanding datasets can help models generalize better to new cases.

Another improvement is integrating advanced deep learning architectures, such as Vision Transformers (ViT) or hybrid CNN–Transformer models, which can capture both spatial and contextual features in MRI images. Combining CNNs with transformer-based models may increase detection accuracy, especially for subtle or small tumors.

Researchers also suggest boosting model robustness through data augmentation, transfer learning, and domain adaptation, enabling models to perform better on unseen MRI scans from different hospitals or scanners. Additionally, multimodal analysis, combining MRI with other imaging types (e.g., CT, PET), could further improve detection reliability.Overall, these enhancements aim to create more accurate,robust, and scalable brain tumor detection systems capable of reliably identifying tumors across diverse real -world medical imaging scenarios.

9. Conclusion

The rapid development of deep learning has significantly advanced medical image analysis, particularly in detecting brain tumors from MRI scans. In this study, a hybrid deep learning system was developed to accurately identify brain tumors.

The system integrates multiple CNN architectures, including VGG16, ResNet18, InceptionV5, and DenseNet121, to extract detailed visual features from MRI images. Combining these models allows the system to detect various tumor patterns that a single model might miss.

An ensemble learning approach was used, combining predictions from individual models through probability averaging (soft voting) and majority voting (hard voting) to produce the final classification. Training on a diverse set of MRI images enabled the system to learn different tumor patterns, improving detection reliability.

Experimental results show that the hybrid framework achieves high accuracy in distinguishing tumor and non-tumor cases. Confusion matrix analysis confirms its effectiveness in reducing misclassification. Furthermore, the inclusion of a user-friendly interface supports real-time detection, making the system practical for clinical use.

Overall, the proposed approach provides an automated, accurate, and scalable solution for brain tumor detection, contributing to enhanced diagnosis and better patient care.

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