Optimizing Brain Tumor Diagnosis: Leveraging Ensemble Techniques with Deep Learning Architectures

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***Abstract*—Brain tumor identification and segmentation are essential components of medical image processing for diagnosis and treatment planning. This work aims to evaluate deep-learning models for brain tumor detection based on MRI images. Five popular deep learning architectures are utilized in the study to assess the ability to accurately diagnose brain cancers: VGG16, VGG19, ResNet-50, MobileNet, and Inception V3. The research highlights the need for accurate segmentation to distinguish benign from malignant tumors. It also examines the limitations of existing techniques and proposes novel ways to overcome these problems. Important metrics including accuracy, sensitivity, specificity, and computational efficiency are measured to gauge how well the models perform. The findings demonstrate the significance of advanced deep-learning techniques for automating the diagnosis of brain tumor.**

***Index Terms*—Brain tumor detection, MRI segmentation, Deep learning, Convolutional Neural Networks, VGG16, VGG19, ResNet-50, MobileNet, Inception Net.**

I. Introduction

Despite advancements in models, identifying and categorizing brain tumors remains challenging due to the complex brain architecture, variances in tumor size, form, location, and noise in medical images. Current models may struggle to generalize across different datasets and may not work well on uncommon or unidentified tumor forms. Genetic mutations, radiation exposure, age, family history, and specific medical diseases increase the risk of brain tumors. Symptoms of brain tumors include headaches, seizures, blurred vision, hearing loss, difficulty speaking or learning, numbness, mood swings, difficulty concentrating, and nausea. It's important to note that not all brain tumors have the same symptoms, as they can be caused by other conditions.

Brain tumor detection techniques need to be reliable, precise, and capable of handling medical imaging data. CNNs, deep learning algorithms, can detect and classify brain cancers using vast volumes of labeled data. However, the choice of architecture, training set, and optimization strategies significantly impact CNN efficacy. Sophisticated image processing methods, such as picture registration, noise reduction, and intensity normalization, can improve the precision of brain tumor identification. Medical imaging-specific feature extraction techniques, such as texture analysis and shape-based features, can yield valuable tumor characterization data. Evaluating the effectiveness of these techniques requires strong assessment measures considering clinical relevance, accuracy, and sensitivity.

This study proposes a novel architecture for brain tumor detection and classification, integrating deep learning models like VGG19, VGG16, ResNet-50, MobileNet, and Inception V3. The architecture creates a comprehensive dataset incorporating medical imaging data and semantic information. Boosting techniques like LightGBM, AdaBoost, CatBoost, Gradient Boosting Decision Trees (GBDT), XGBoost, and AdaBoost can be employed to predict tumor characteristics and classify brain tumor types. Combining boosting algorithms with deep learning models allows for more precise predictions about tumor characteristics and types, ensuring accurate, diverse, and tailored classification results. The study aims to demonstrate how the proposed recommendation architecture can offer personalized and accurate brain tumor detection and classification through empirical validation and comparative analysis. This research aims to advance diagnostic systems in the medical domain, enhancing diagnostic accuracy, facilitating early detection, and improving patient outcomes.

The major contributions of the work are:

- The study focuses on evaluating the effectiveness of

five popular deep learning architectures, namely VGG16, VGG19, ResNet-50, MobileNet and Inception V3, in accurately detecting brain tumors. By systematically assessing these models, the study provides insights into their strengths and limitations in the context of brain tumor detection.
- The study acknowledges the challenges inherent in identifying and categorizing brain tumors, such as the complex brain architecture, variations in tumor characteristics, and noise in medical images. By recognizing these challenges, the research aims to propose novel methodologies to overcome them, thereby enhancing the accuracy of tumor identification.
- The study employs key metrics such as accuracy, sensitivity, specificity, and computational efficiency to comprehensively evaluate the performance of the deep learning models. By comparing these metrics, the research provides insights into the relative efficacy of different architectures in brain tumor detection tasks.

II. Related Work

This chapter contains a study of the literature review carried out in accordance with the research's specifications. The literature evaluation for this study entails a detailed examination of 20 academic publications that were published between 2017 and 2023.

Solanki et al.[9] provide an overview of brain tumor detection and classification using intelligence techniques, focusing on MRI imaging. Their exploration encompasses deep learning models, traditional methods, and various medical imaging modalities, utilizing the BRATS 2018 dataset. The study highlights advancements such as deep models, 3D models, and attention-based mechanisms for improved segmentation outcomes and reduced computational complexity.] Menachery et al.[5]present a study on brain tumor detection using a deep learning model to explore research techniques in this domain. Their approach involves Berkeley's wavelet transformation and a deep learning classifier trained on a Kaggle dataset. The model achieved training accuracies of 85.30% for ResNet50, 78% for DenseNet201, 78% for Inception V3, and 77.12% for MobileNet. Reddy et al.[7] implement the latest deep learning techniques for brain tumor identification from MRI images to enhance accuracy and speed. Their approach involves SVM and CNN models trained on the BRATS-2020 dataset. However, specific accuracy values are not provided, and the study lacks a comprehensive dataset and clinical validation.Sravya v et al.[10]conduct a survey on brain tumor detection using machine learning and deep learning algorithms, focusing on identification and classification. Employing K-Means clustering, SVM, CNN, DCNN, and DNN, they analyze the BRATS 2018 dataset, achieving accuracies of 98%, 86.7%, and 87% for CE-T1W, SCGAGMM, and ADI, respectively. The study highlights challenges in data preprocessing, complexity in segmentation. Krittika Jain et al. [3]present a hybrid technique for brain tumor detection and classification using MRI scans. Their approach combines segmentation techniques, feature extraction, and classification methods to achieve high accuracy. However, the method is more complex and requires extensive computations, limiting its practical applicability. Alsubai et al.[2]propose ensemble deep learning for brain tumor detection to enhance detection and classification performance. Utilizing VGG, ResNet, and AlexNet on a Kaggle dataset, their CNN-LSTM model achieves 99.1% accuracy in detecting brain tumors. However, limitations include the inability to distinguish between abnormal and normal tissues and identify lesions, indicating areas for improvement. Sapra et al. [8] presents a study on brain tumor detection using a modified probabilistic artificial neural network structure. Their approach integrates image processing algorithms with the ANN structure, utilizing a dataset of 64 patients' MRI images. The model achieves 100% accuracy in brain tumor classification, yet limitations include a lack of accuracy variability, computational efficiency concerns, data quality dependencies, and the inherent complexity of medical imaging analysis. Laddha and Ladhake [4] review brain tumor detection methods focusing on segmentation and threshold operations to enhance image quality. Their study proposes applying threshold and segmentation techniques alongside effective algorithms for image quality improvement based on wavelets for CT/MRI data. However, the review lacks comparison, quantitative results, and raises concerns about its generalizability. Mohsen et al.[6]investigate brain tumor classification using deep learning neural networks (DNN) and Fuzzy C-means. Their study aims for high accuracy and compares the performance with traditional classifiers. Utilizing 66% real human brain MRI images, their approach outperforms traditional methods in accuracy, recall, precision, and AUC. However, limitations include a small dataset, lack of external validation, and detailed comparisons with other methodologies. Alqudah et al.[1] focus on brain tumor classification using MRI images, comparing CNN models with different image processing techniques. Employing Alexnet CNN and NS-CNN, they analyze 3064 T1 weighted contrast-enhanced brain MR images. Their CNN model achieves high accuracy ranging from 87.38% to 98.4%, yet the evaluation is limited to a specific dataset, warranting further validation on diverse datasets.

From all the above studied papers,limitations identified include:

- Research heavily relies on specific datasets, such as Kaggle or BRATS 2018, which may not be applicable to other situations or clinical contexts, potentially affecting model performance.
- Certain models excel in accuracy but struggle to differentiate between abnormal and normal tissues, a critical issue for informed healthcare decisions. Future research should focus on developing more precise models.
- Research lacks clinical validation and external datasets, making it challenging to assess the robustness and practical application of suggested approaches without comprehensive evaluation.
- Computationally intensive methods like hybrid and en-

semble models may be limited in real-time clinical settings due to their complexity. Developing more efficient algorithms could enhance their applicability.

III. Proposed Methodology

The brain tumor detection system is developed using medical imaging data from kaggle. Deep learning architectures like VGG19, VGG16, ResNet, MobileNet, and Inception are used to analyze MRI images for improved detection accuracy. Ensemble learning techniques like XGBoost, AdaBoost, CatBoost, GBDT, and LightGBM are integrated to refine the detection process. This comprehensive approach aims to deliver accurate diagnoses, facilitate early intervention, and improve patient care and prognosis. The system provides healthcare professionals with tailored assessments, ultimately improving patient care and prognosis.

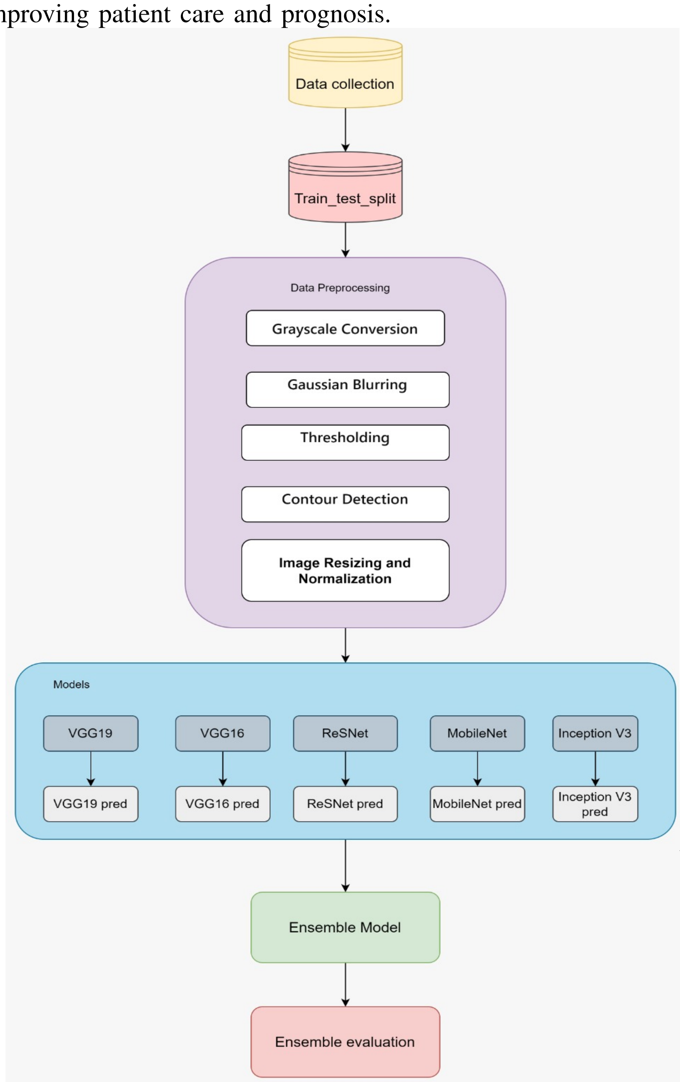

Figure-1:Methodology

A. Data Collection

Collecting the data: In the proposed research methodology, the initial step involves collecting a brain tumor dataset from publicly available repositories to serve as the primary input for the classification system. This entails accessing reputable sources housing datasets containing MRI images of brain tumors, including glioma, meningioma, pituitary tumors, and non-tumor samples. The anticipated outcome is the acquisition of a comprehensive dataset comprising essential attributes such as MRI images, tumor types, and corresponding labels. This dataset will serve as the foundational resource for training, validating, and optimizing the brain tumor classification system, facilitating further exploration and analysis within the research framework.

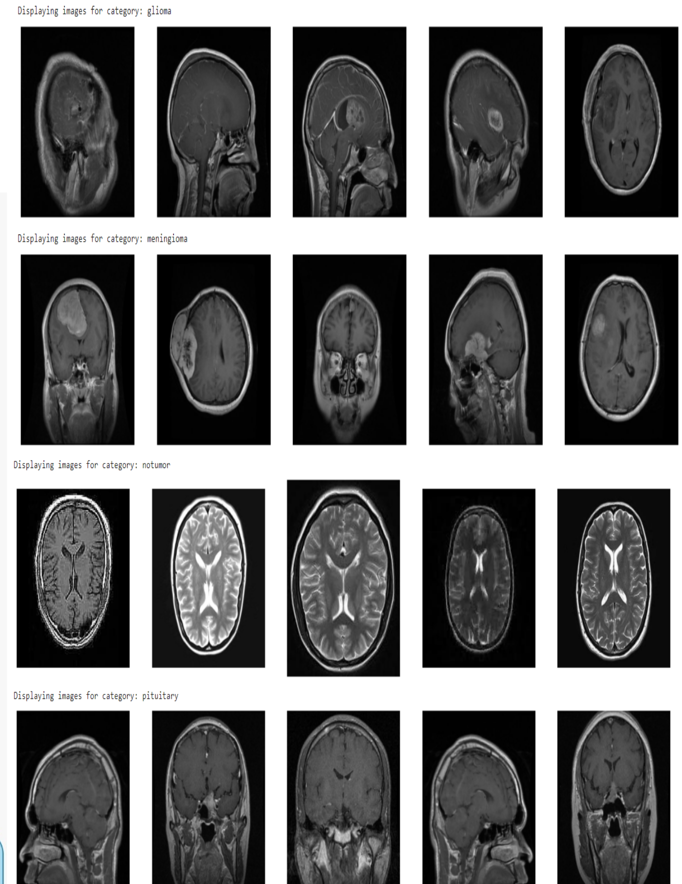

Figure-2: sample images from the dataset.

B. Train-test-split

The train_test_split function from scikit-learn divides a dataset into training and testing sets, with 30% for testing and 70% for training. The function creates subsets of the data with desired sizes using random selection and replace=False. These subsets are then indexed into the original data arrays, reducing the dataset size to the desired size. The shapes of the new subsets are printed to confirm the subset creation process, indicating the dimensions of the image data and label arrays. This process ensures reproducibility and efficient data management.

C. Data Preprocessing

Preprocessing is crucial for brain tumor detection and classification due to its noise reduction, feature extraction, normalization, and dimensionality reduction techniques. These techniques enhance the clarity of medical imaging data, making it easier to identify tumor features. They also ensure consistent image format and scale, allowing deep learning models to learn effectively. The dimensionality of the data is reduced by removing irrelevant features or noise, leading to more efficient modeling. Preprocessing also improves model performance by preparing data in a clean and standardized format, resulting in more accurate and reliable results.

The process involves converting an input image from color to grayscale, applying Gaussian blurring to reduce noise and smooth irregularities, thresholding the image to create a binary image, and performing morphological operations like erosion and dilation. Contours are detected to represent object boundaries and are useful for further analysis. Extreme points are identified to define a bounding box around the region of interest, which helps crop the relevant portion of the image. A rectangular region of interest is cropped from the original image using extreme points, is isolated for further processing. The cropped image is resized to a consistent size to ensure uniformity and compatibility with the model architecture. The resized image is normalized using cv2.normalize(), which scales pixel values to a range, stabilizing the learning process during model training by ensuring consistent input data.

D. Models

In the context of brain tumor detection using deep learning, several pre-trained convolutional neural network (CNN) architectures, including VGG19, VGG16, ResNet, MobileNet, and InceptionV3 are utilized. Here's an overview of each of these models and their potential applications in brain tumor detection:

- VGG19: VGG19, a 19-layer architecture, is known for its simplicity and uniformity. It's used in brain tumor detection for feature extraction from MRI images, capturing intricate patterns and textures, aiding in tumor identification.
- VGG16: VGG16, a 16-layer VGG architecture developed by the Visual Geometry Group, uses small 3x3 filters and max-pooling layers for feature extraction. Despite being slightly less complex than VGG19, VGG16 offers powerful feature extraction capabilities, particularly in brain tumor detection, identifying tumor-related patterns in MRI images.
- ReSNet: Microsoft Research's ResNet is a CNN architecture that uses residual learning to improve brain tumor detection accuracy. It comes in depths like ResNet-18, 34, and 50, with deeper variants containing more layers. ResNet's deep architecture and residual connections can effectively capture hierarchical features in MRI images.
- MobileNet: MobileNet is a lightweight CNN architecture developed by Google, especially for efficient deployment on embedded and mobile devices. Depthwise separable convolutions are utilized to maintain performance and reduce computational complexity. It comes in many sizes and is highly useful for real-time brain tumor detection applications.
- Inception V3:Google's InceptionV3 is a CNN architecture that uses multiple parallel convolutional pathways with different filter sizes to efficiently capture multi-scale features. Its multi-scale feature extraction capabilities can be beneficial in brain tumor detection, potentially improving detection performance in MRI images. The best model to use in the classification system was chosen after consideration of each model's performance on the test dataset, which provided information about the models' respective benefits and drawbacks.

E. Model Evaluation

The model evaluation assesses the effectiveness of an ensemble model in the brain tumor detection and classification system using metrics like accuracy, precision, and F1 score. These metrics evaluate the model's ability to accurately classify brain tumors and distinguish between different tumor types. By comparing individual models and ensembles, optimal classification strategies can be identified. The ensemble model combines the strengths of multiple base models, such as VGG19, VGG16, ResNet, MobileNet, and InceptionV3, improving diagnostic accuracy and patient outcomes.

TABLE I
MODELS EVALUATION

Model	**Accuracy**
VGG19	0.8757
VGG16	0.8787
ResNet	0.6909
MobileNet	0.9499
Inception V3	0.9242

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

About Dataset:

The Brain Tumor Detection Dataset comprises 7,023 instances of human brain MRI images, categorized into four distinct classes: glioma, meningioma, no tumor, and pituitary. Preprocessing procedures have been implemented to ensure data integrity, thereby enhancing model performance and accuracy. This dataset is intended to facilitate advancements in brain tumor detection through machine learning and ensemble modeling techniques, enabling personalized and precise diagnoses.

Evaluation Metrics:

TABLE II
VGG19 EVALUATION

	precision	**recall**	**f1-score**	**support**
glioma	0.85	0.85	0.85	149
meningioma	0.81	0.73	0.77	135
notumor	0.94	0.96	0.95	173
pituitary	0.87	0.91	0.89	173

Table 2 displays the performance in classifying brain MRI images across four classes. The model achieved high precision, recall, and F1-score values, indicating its effectiveness in accurately classifying brain MRI images for tumor detection. The model achieved a precision of 0.85 for glioma, indicating 85% of images classified as glioma were correctly identified. The F1-score, the harmonic mean of precision and recall, provides a balance between the two metrics. The model's support indicates the distribution of data across different classes.

TABLE III
VGG16 EVALUATION

	precision	recall	f1-score	support
glioma	0.90	0.85	0.88	149
meningioma	0.72	0.89	0.79	135
notumor	0.99	0.91	0.95	203
pituitary	0.90	0.86	0.88	173

Table 3 presents evaluation metrics for brain tumor classification, achieved high precision and F1-score in the ”no tumor” class, with precision of 0.99, recall of 0.91, and F1-score of 0.95. VGG16 also performed well for glioma, meningioma, and pituitary tumor classification, particularly in detecting images without tumors.

TABLE IV
RESNET EVALUATION

	precision	recall	f1-score	support
glioma	0.54	0.73	0.62	149
meningioma	0.59	0.30	0.40	135
notumor	0.92	0.91	0.93	203
pituitary	0.64	0.66	0.65	173

Table 4 presents the ResNet model's evaluation metrics for brain tumor classification are presented in a table. The model achieved a precision of 0.54, recall of 0.73, and F1-score of 0.62 for glioma, 0.59, 0.30, and 0.40 for meningioma, 0.92, 0.91, and 0.93 for images without tumors, and 0.64, 0.66, and 0.65 for pituitary tumor classification. However, the model struggles with meningioma classification, indicating lower performance compared to other models.

TABLE V
MOBILENET EVALUATION

	precision	recall	f1-score	support
glioma	0.95	0.90	0.93	153
meningioma	0.88	0.95	0.91	155
notumor	0.99	0.99	0.99	171
pituitary	0.98	0.96	0.97	181

Table 5 evaluates the MobileNet model for brain tumor classification using precision, recall, F1-score, and support metrics. The model achieved high precision for glioma, meningioma, meningioma, no tumor, and pituitary tumor. The F1-score measures the harmonic mean of precision and recall. The model demonstrated strong performance across all classes, with a particularly high precision, recall, and F1 score for the ”no tumor” class.

TABLE VI
INCEPTION V3 EVALUATION

	precision	recall	f1-score	support
glioma	0.93	0.91	0.91	153
meningioma	0.88	0.85	0.87	155
notumor	0.96	0.98	0.97	171
pituitary	0.93	0.95	0.94	181

Table 6 presents evaluation metrics for the Inception V3 model for brain tumor classification using precision, recall, and F1-scores. The model achieved high precision, recall, and F1 scores for glioma, meningioma, no tumor, and pituitary tumors. For glioma, it achieved a precision of 0.93, a recall of 0.91, and an F1-score of 0.91. For meningioma, it achieved precision, recall, and F1-scores of 0.88, 0.85, and 0.87, demonstrating its effectiveness across all classes.

The study compared different models for brain tumor classification, revealing varying levels of precision, recall, and F1 score. VGG16 showed high precision and F1 scores across glioma, meningioma, and pituitary tumor classes. ResNet showed moderate performance, particularly in meningioma classification. MobileNet demonstrated high precision, recall, and F1-score across all classes, especially for images without tumors. Inception V3 and MobileNet showed strong performance across all classes. Combining these models can enhance classification accuracy and robustness.

TABLE VII
ENSEMBLE MODEL EVALUATION

	precision	recall	f1-score	support
glioma	0.95	0.92	0.93	153
meningioma	0.90	0.92	0.91	155
notumor	0.98	0.99	0.99	171
pituitary	0.97	0.97	0.97	181

In response to the observed variations in performance among individual models, we propose the implementation of an ensemble approach in our brain tumor detection system. This ensemble classifier will integrate VGG16, Inception V3, and MobileNet models to capitalize on their respective strengths and collectively enhance the system's tumor detection accuracy. The ensemble approach, combining VGG16, Inception V3, and MobileNet models, enhances the accuracy, precision, recall, and F1-score values of our brain tumor detection system, providing clinicians with reliable diagnoses and potential applications in medical imaging.

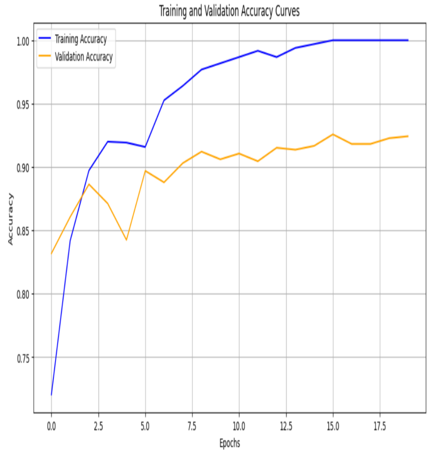

Figure-3: Accuracy curve of the ensemble model.

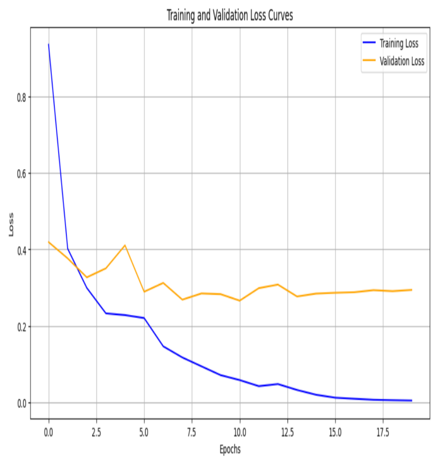

Figure-4: Loss curve of the ensemble model.

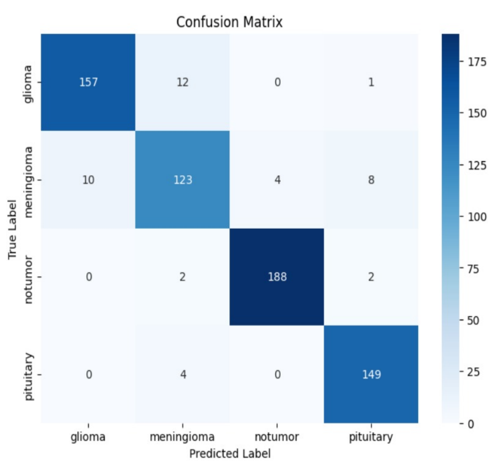

Figure-5: Confusion matrix of the ensemble model.

V. Conclusion

Our research concludes by highlighting the critical role that ensemble techniques play in improving the diagnostic precision of brain tumor detection systems. We have achieved a considerable improvement in tumor identification accuracy by including deep learning models, such as VGG19, VGG16, Inception V3, and MobileNet. MobileNet and Inception V3 are coupled to create an ensemble classifier. Notably, our ensemble model successfully detects brain tumors with an overall accuracy of 95%, demonstrating its effectiveness.

Moreover, it is significant that the ResNet model performed somewhat worse than models like as VGG19, VGG16, MobileNet, ResNet and Inception V3, which all obtained accuracies of up to 87%. This finding emphasizes how crucial it is to properly choose and include models in ensemble techniques to maximize performance across various tumor types and datasets. The ensemble technique demonstrated high accuracy, precision, recall, and F1-score, indicating potential for early neurosurgery diagnosis and treatment planning. This study utilizes deep learning models, improving patient outcomes and practice efficiency in medical imaging, thereby enhancing personalized brain tumor identification and clinical care.

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