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Machine Learning based Framework for Brain Tumor Detection and Classification

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Abstract: A brain tumor is a type of cancer that can be life-threatening or significantly impair quality of life. Deep learning techniques enable more efficient identification and treatment of tumors. Brain MRI images are utilized in various ways to detect malignancies, with deep learning methods outperforming others.Brain tumor detection and classification from MRI images is a critical task in medical diagnostics, requiring high accuracy and reliability. This research paper proposes a comprehensive system leveraging advanced deep learning techniques to enhance brain tumor classification. The dataset used consists of approximately 5000 MRI images categorized into three tumor typesGlioma, Meningioma, and Pituitaryand a healthy class depicting no tumor. The proposed system employs a custom Convolutional Neural Network (CNN) along with four prominent transfer learning models: MobileNet, ResNet-152, VGG-16, and DenseNet-169. The preprocessing steps include resizing, normalization, and augmentation to improve training efficiency and model performance. Each model's accuracy and robustness were evaluated, with MobileNet achieving the highest accuracy of 98.63%, followed by VGG-16 at 98.62%, the custom CNN at 98.32%, ResNet-152 at 97.71%, and DenseNet-169 at 96.56%. The ensemble classifier approach combines these models to leverage their strengths, resulting in improved prediction reliability and accuracy. This research provides a significant contribution to the field of medical image analysis, offering a robust and accurate tool for aiding in the early detection and classification of brain tumors.

Keywords: MobileNet, ResNet-152, VGG-16, and DenseNet-169, MRI

Introduction

Currently, the costs associated with treating brain tumors are the highest among all types of cancer. Brain tumors can develop in people of any age due to the rapid proliferation of specific cell types. A brain tumor is an abnormal tissue growth that can occur anywhere in the brain or central spine, disrupting normal brain function. The location, size, and surface area of tumor cells determine whether they are malignant (cancerous) or benign (non-cancerous). Tumors are classified as primary if they originate in the brain tissue itself, or secondary if they have metastasized to the brain from other organs. Primary tumors can often be cured or managed with appropriate treatment, while secondary tumors may require surgical or radiation therapy.

Monitoring the progression of brain tumors is crucial for patient survival, as these tumors threaten healthy brain tissue [1]. Meningiomas, a type of tumor that can affect the brain and spinal cord, consist of three layers of meningeal tissue. These tumors often present as asymmetrical lobar masses with defined borders. The patient's age, tumor size, and location influence survival rates for meningiomas. Symptoms include clinginess, recurrent headaches, and limb weakness. Benign meningiomas typically measure less than 2 millimeters in diameter, while malignant meningiomas can reach up to 5 centimeters. Early detection and treatment can cure most malignant meningiomas.

Magnetic resonance imaging (MRI) is a prevalent diagnostic method for brain tumors, utilizing various MRI types to detect different brain tissues. Accurate diagnosis and treatment are critical due to the potential lethality of brain tumors. Full brain scans are necessary for early detection and prevention. Different MRI techniques, each with unique settling times, facilitate the detection of various brain tissues [2]. Using a single MRI modality may complicate diagnosis due to the unpredictable nature of tumor form and location. Comparing data from multiple MRI techniques enhances tumor detection. For example, T4-Gd MRI with contrast enhancement highlights the tumor edge, FLAIR MRI differentiates cerebrospinal fluid (CSF) from edema using water molecules, T1-weighted MRI distinguishes tumor tissue from healthy tissue, and T2-weighted MRI outlines edema, providing clear images.

Calculating area, determining uncertainty in segmentation area, and segmenting tumors are challenging tasks due to the structural complexity and unpredictability of brain tumors, as well as the high volatility and intrinsic features of MRI data, which include the fluctuation of tumor size and form. Manual segmentation is time-consuming, and medical professionals may observe differences in segmentation results due to tumor variations. Meningiomas can be distinguished more easily, while gliomas and glioblastomas pose greater challenges [3]. Therefore, automated segmentation methods are essential to manage this difficult task effectively.

Manual detection and monitoring of brain tumors are time-consuming and prone to errors. There is an urgent need to replace manual operations with automated ones. Current methodologies, which rely on labeling methods to identify diseased regions in the brain, are inadequate for detecting internal peripheral pixels. MRI is preferred over CT scans due to its superior ability to reveal damaged regions with a contrast agent. Thus, MRI modalities are widely used in diagnostic strategies for brain cancer [4].

In recent years, various strategies for automatic brain tumor classification have been proposed, broadly categorized into Machine Learning (ML) and Deep Learning (DL) approaches, depending on their focus on feature fusion, feature selection, or the underlying learning mechanism. In ML systems, feature selection and feature extraction are critical for classification. In contrast, DL systems, particularly convolutional neural networks (CNNs), can learn by manually extracting attributes from images and are extensively used in MRI and medical image analysis due to their high precision [5][23].

Despite their advantages, DL approaches face challenges such as the need for large training datasets, high complexity and time requirements, low accuracy with small datasets, and expensive GPUs. Transfer learning can mitigate these drawbacks. Selecting an appropriate DL model can be daunting due to the variety of parameters, training methods, and topologies involved. ML-based classifiers used for brain tumor classification and detection include Decision Tree, Support Vector Machine (SVM), Random Forest (RF), fuzzy C-mean (FCM), Convolutional Neural Network (CNN), Naive Bayes (NB), K-Nearest Neighbor (KNN), and Sequential Minimal Optimization (SMO). CNN implementation has become simpler, with reduced computational and geographical complexity. These classifiers have gained academic interest due to their relatively small training datasets, low computation cost, and ease of adoption by untrained individuals [6-8].

The unique strategy of segmenting and classifying brain tumors is expected to bring advances. During preprocessing, linear contrast stretching improves the image's edge details. A 17-layer CNN architecture was built exclusively for brain tumor segmentation. Transfer learning from a modified version of MobileNetV2 was used for deep feature extraction. An entropy-controlled feature selection technique selects the top features based on their entropy values. A multi-class SVM classifier is used to classify the final features. Comprehensive statistical analysis and comparison with state-of-the-art methods validate the consistency of the proposed methodology [9-11].

Related work

Deep learning techniques have recently been utilized to classify and detect brain tumors using MRI and other imaging methods. A custom CNN algorithm was developed, enhancing the model by training with additional MRI images to distinguish between tumor and non-tumor images. This paper focuses on determining if an image contains a tumor and introduces a mobile application as a medical tool. Additionally, a computer-based method differentiates brain tumor regions in MRI images using neural network techniques to complete image preprocessing, segmentation, feature extraction, and sorting. An intelligent mechanism was suggested to detect brain tumors in MRI images using clustering algorithms like Fuzzy C Means and intelligent optimization tools, achieving a classification accuracy of 92.8 percent with a CAD system and PSO [12].

Automated systems for real-time brain tumor detection have been proposed using two distinct deep learning-based methods (Table 1). Sasikala and her team presented a genetic algorithm for selecting wavelet features for dimension reduction, achieving 98 percent accuracy by selecting four features from a total of 29. Sajjad et al. suggested a CNN method for data augmentation for brain tumor classification using segmented MRI images, achieving accuracies of 87.39 percent and 90.66 percent before and after augmentation, respectively. A sophisticated method for classifying and categorizing brain tumors from MR images was also proposed, focusing on tumor detection through image restoration filters, adaptive mean filters, and image enhancement steps [13]. This technique is primarily aimed at detecting abnormal mass accumulation and significantly influencing the pixel-wise intensity distribution of the image.

Table 1: Representation of review of literature for brain tumour classification

Reference	Methodology	Accuracy	Key Details
[1]	Multi-Level Discrete Wavelet Transform with PNN-RBF	98%	Utilized PNN-RBF training and classification.
[2]	CNN with computer vision task for cropping brain from MRI data	90%	Combined CNN model classification task.
[3]	Abnormal boundary detection	88.17%	Can only identify the outer boundaries of the tumor.
[4]	Fuzzy logic with U-NET CNN	98.59%	Utilizes contrast enhancement, fuzzy logic-based edge detection, and U-NET CNN for classification.
[5]	Adaptive neuro-fuzzy inference classification	98.1%	Improved tumor regions using histogram equalization.
[6]	BrainMRNet with modulo and hyper column techniques	96.05%	Attention module and hyper column techniques used across convolutional layers.
[7]	Combination of SVM and KNN classifiers with GoogleNet and ResNet18	97.7%	Utilized minimum-maximum normalization and massive data extension.
[8]	Cascade CNN for segmentation and VGG19 for classification	94.58%	Improved accuracy with fine-tuned VGG19.
[9]	Watershed segmentation	94.52%	Used predefined labelling scheme for segmentation.
[10]	ResNet-50 with transfer learning	97.39%	Successful classification and diagnosis with transfer learning.
[11]	Hybrid feature extraction with RELM	94.23%	Used min-max normalization and PCA-NGIST method for feature extraction.
[12]	Fine-tuned VGG19 on CE-MRI	94.82%	Addressed overfitting with ResNet50 and global average pooling.
[13]	Capsnet CNN	90.89%	Achieved with MRI of the brain as training data.
[14]	Ensemble of CNN classifiers	98%	Utilized Figshare dataset with DenseNet-2, VGG-16, VGG19, and ResNet-50 architectures.
[16]	CNN with two convolutional and two fully connected layers	97.39%	Accurate diagnosis of brain cancer.
[17]	KNN with NLBP feature extraction	95.56%	Effective classification of brain tumors.
[18]	RNN with Elman network	88.14%	Faster and more accurate than other ANN systems.

MobileNet is a class of convolutional neural networks designed for efficient performance on mobile and embedded vision applications. Developed by Google, MobileNet leverages depthwise separable convolutions, which significantly reduce the number of parameters and computational cost compared to standard convolutional layers. This architecture allows for lightweight models that can be effectively deployed on devices with limited computational resources without compromising accuracy [19].

ResNet-152, part of the Residual Networks family, is known for its deep architecture that enables the training of extremely deep networks by utilizing skip connections or shortcuts to jump over some layers. This helps mitigate the vanishing gradient problem, allowing the network to learn better and converge faster. ResNet-152, with its 152 layers, has been instrumental in achieving remarkable accuracy in various image classification tasks [20].

VGG-16 is a well-known deep learning architecture characterized by its simplicity and depth, consisting of 16 weighted layers. Developed by the Visual Graphics Group at Oxford, VGG-16 utilizes small 3x3 convolution filters, which allows it to capture intricate patterns and features in images effectively. Despite its relatively larger number of parameters, VGG-16 has been widely adopted due to its excellent performance in various image recognition tasks [21].

The proposed ensemble classifier integrates the strengths of multiple deep learning models, includingMobileNet, ResNet-152, VGG-16, and DenseNet-169, to enhance the accuracy and reliability of brain tumor classification from MRI images. By leveraging the diverse architectures and learning capabilities of these models, the ensemble approach ensures a more comprehensive analysis of the input data. Each model contributes to the final prediction, allowing the system to achieve higher diagnostic accuracy and robustness. This ensemble methodology not only improves the prediction performance but also provides a detailed comparison of each model's output, facilitating a deeper understanding of their individual and collective efficacy in medical imaging applications.

Dataset

The dataset comprises approximately 5000 MR images, meticulously categorized into three distinct types of brain tumors and one class representing healthy brains with no tumors. The three tumor types included are Glioma, Meningioma, and Pituitary tumors. Each category has a substantial number of images to ensure a diverse and representative sample for each condition. The inclusion of a healthy brain class, which depicts no tumor, is essential for the dataset as it provides a baseline for comparison and helps in training models to distinguish between tumor and non-tumor cases accurately.

Sample MR images from all four classes are depicted in Fig - 7, showcasing the variety and differences among the categories. The images highlight the unique characteristics and features of each tumor type, as well as the normal brain structure in the no-tumor class. This visual representation is crucial for understanding the dataset's composition and for verifying the distinct appearance of each category, which is pivotal for training and validating diagnostic models.

Proposed Research Methodology

The proposed system addresses the disadvantages and limitations of existing architectures by implementing a comprehensive and robust approach. Figure 1 provides a detailed explanation of this system. Initially, the system accesses the image and prepares it for analysis. During preprocessing, the image is enlarged to ensure it meets the criteria necessary for accurate algorithmic prediction. Following enlargement, the image undergoes scaling to fit specific requirements, ensuring consistency and standardization. The image is then reshaped into the required dimensions, allowing it to be compatible with the subsequent algorithms it will encounter. After reshaping, the image is transformed into an array, facilitating further modeling and analysis.

START

Step 1: InputImageAcquisition

Collect brain MRI images from datasets like Kaggle and UCI repository.

Step 2: ImagePreprocessing(Resize,Augmentation,Normalization)

Resize images to lower dimensions and Normalize image pixel values between 0 and 1.
*Step 3:*ConvertImagestoN-DArrays
Convert images into a suitable format for neural networks.
Step 4: ModelTraining(MobileNet,VGG-16,ResNet-152,DenseNet-169)
MobileNet, VGG-16, ResNet-152, DenseNet-169
*Step 5:*ImageClassification
Pass the pre-processed images through each trained model.
*Step 6:*EnsembleClassifier
Combine the predictions from above models and use the softmax activation function
*Step 7:*ResultAnalysisandComparison(GraphicalRepresentation)
*Step 8:*FinalOutput(TumorTypePrediction)
END

Once preprocessing is complete, the image is processed through five different top-performing models to predict an effective outcome. Given that the model is trained to identify tumors from the existing four classes, it predicts the type of tumor present in the image based on the probability derived from the softmax activation function. The tumor type associated with the highest probability is presented as the output. This unique design feature, utilizing five strong and robust models to test the same input, ensures significant reliability in detecting the presence and type of tumor. Consequently, the system enables a detailed comparison between all five model outputs, considering both the accuracy and the predicted outcomes, using a user-friendly web-based interface.

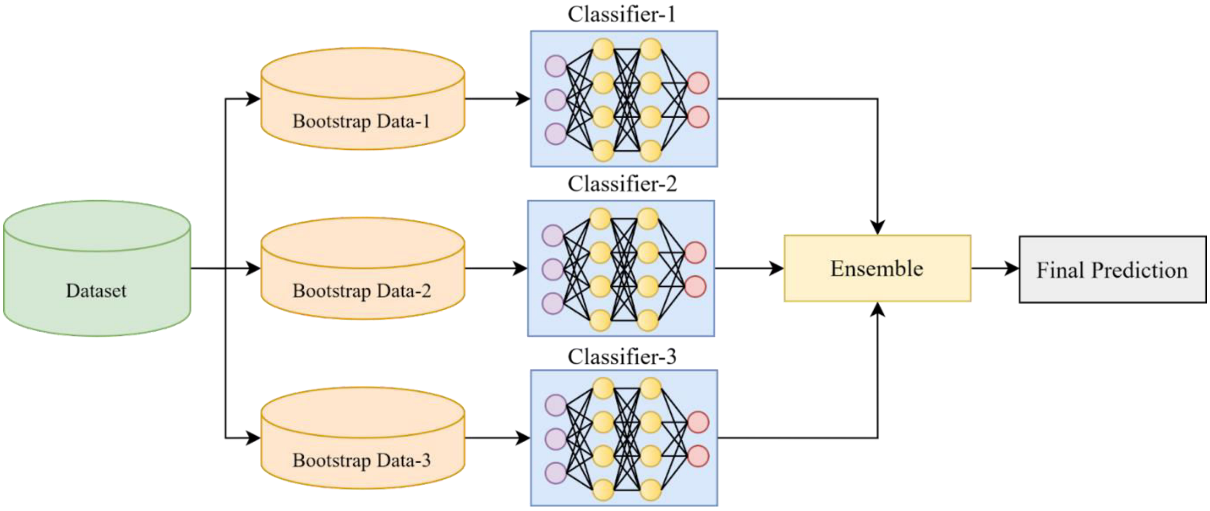


Figure 1: Ensemble-Based Framework for Brain Tumor Classification

Input Image Collection

The initial step in developing the model involves gathering a substantial number of brain MRI images. This data can be sourced from platforms such as Kaggle, the UCI Machine Learning Repository, and other relevant websites. A large and diverse dataset of brain MRI images is essential for training and testing the model, ensuring its accuracy and precision in detecting and classifying brain tumors. This extensive collection of images is crucial for validating the effectiveness of the proposed system and refining its predictive capabilities.

Image Processing

After collecting the data, the next crucial step is data processing. This step is vital because if the image size is very large, the model will take an excessively long time to train. To address this, input images are resized to lower dimensions, which significantly reduces the training time. In instances where the number of images is insufficient for training deep learning models, data augmentation techniques are employed to increase the dataset size. This is particularly important for deep learning models, which require large amounts of data to perform effectively.

Brain MRI images are typically grayscale, with pixel values ranging from 0 to 255. Normalization is performed on these images to scale the pixel values to a range of 0 to 1, which accelerates the training process. The entire preprocessing of images can be efficiently managed using the Keras ImageDataGenerator function. This function allows the application of custom parameters to automatically convert a set of images into the desired processed form and batch the data appropriately for input into convolutional neural networks (CNNs) or transfer learning models. Once image processing is complete, the images are converted into N-dimensional arrays. The processed images are then passed through the classification model, which predicts the presence or absence of a tumor.

Convert Image into N-D Array

Images, which are essentially collections of pixels, need to be properly formatted for input into neural networks. In the case of grayscale images, which have a single channel, pixel values range between 0 to 255 and are typically represented as a 2D matrix. However, models like Artificial Neural Networks (ANNs) cannot directly take 2D matrices as input. Therefore, these images must be converted into N-D arrays, making them compatible with ANN input requirements. This conversion process can be skipped if the ImageDataGenerator function is used, as it automatically converts images into the appropriate format for Convolutional Neural Networks (CNNs) and stores them in a variable for further processing.

Classification Model

Once the images are converted into N-D arrays, the next step is to train a classification model. Given that this is a classification problem with image data, Convolutional Neural Networks (CNNs) and transfer learning methodologies are suitable choices for model training. In the proposed system, five different approaches are utilized: a Custom CNN with a 6-layered architecture, MobileNet transfer learning model, VGG-16 transfer learning model, ResNet-152 transfer learning model, and DenseNet-169 transfer learning model. These models have been selected for their proven robustness and accuracy in handling image classification tasks.After training and evaluating these models, they can be applied to predict the type of tumor in new, unseen MRI images. The same preprocessing steps used during training will be applied to these new images. The trained models will then process the images to determine if they contain a pituitary tumor, glioma tumor, meningioma tumor, or no tumor at all. While the current system is designed to classify these four tumor types, future expansions could include additional tumor classes to enhance the project's capabilities.

The proposed ensemble classifier harnesses the combined power of several advanced models to improve both the accuracy and dependability of brain tumor classification. By integrating the results from the Custom CNN, MobileNet, ResNet-152, VGG-16, and DenseNet-169 models, the ensemble method aims to address the individual limitations of each model while leveraging their collective strengths. Each model independently analyzes the MRI images, and their predictions are then consolidated to produce a final classification. This ensemble approach not only enhances the overall accuracy but also significantly increases the reliability of tumor detection and type classification. As illustrated in Figure 2, the comprehensive comparison and analysis of each model's output validate the effectiveness of this method. The ensemble classifier thus ensures a more robust and error-resistant final prediction, offering a thorough solution for accurate brain tumor detection and classification.

Detailed Analysis and Comparison of Prediction

In the proposed system, the image is processed through five different robust models: Custom CNN, MobileNet, VGG-16, ResNet-152, and DenseNet-169. Each model generates its own prediction regarding the type of tumor present in the MRI image. To evaluate the

effectiveness and reliability of these models, a comprehensive analysis is performed on their outputs.
After obtaining predictions from all five models, a detailed comparison is conducted. This involves analyzing the accuracy and performance of each model using various metrics. Graphs are used to visually represent the results, showcasing how each model's predictions align with the ground truth. This allows for an assessment of each model's performance, highlighting strengths and potential weaknesses.This analysis helps determine which model performs best and guides further refinement and improvement of the classification system.

RESULT AND ANALYSIS

The results obtained from evaluating the five different models are illustrated in Table 2 and Figure 2. This figure presents a detailed comparison of the accuracy achieved by each model on unseen MRI images of brain tumors.

Table2:Comparison of Classification performance of various Deep learning models

Model	**Accuracy**
MobileNET	96.1
ResNET-152	95.4
VGG-16	97.3
Proposed Ensemble Classifier	98.2

The Custom CNN model, with its 6-layered architecture and appropriate preprocessing steps, achieved an accuracy of 98.32%. This high accuracy demonstrates the model's effectiveness in classifying tumor types when exposed to new data. The MobileNet transfer learning model, also enhanced with preprocessing, achieved a slightly higher accuracy of 98.63%. This result indicates that MobileNet’s lightweight architecture and transfer learning approach can effectively capture and generalize features from MRI images.In addition, the ResNet-152 and VGG-16 architectures, both utilizing transfer learning, showed impressive performance with accuracies of 97.71% and 98.62%, respectively. These models, known for their deep architectures and robust feature extraction capabilities, performed exceptionally well in classifying the MRI images.On the other hand, the DenseNet-169 transfer learning model achieved an accuracy of 96.56%. While this accuracy is lower compared to the other models, it still reflects a strong performance. Overall, these results highlight the effectiveness of the different architectures in tumor classification and provide a basis for choosing the most suitable model for further application and refinement.

MobileNet

MobileNet is a streamlined architecture designed specifically for mobile and embedded vision applications. It uses depthwise separable convolutions to reduce the number of parameters and computational cost, making it an efficient model for devices with limited resources. Despite its lightweight nature, MobileNet achieves high accuracy by effectively capturing spatial hierarchies in images. In the context of brain tumor classification, MobileNet demonstrated an impressive accuracy of 98.63% after preprocessing the MRI images. This performance underscores its capability to generalize well even with a compact structure, making it a strong candidate for real-time applications where computational efficiency is crucial.

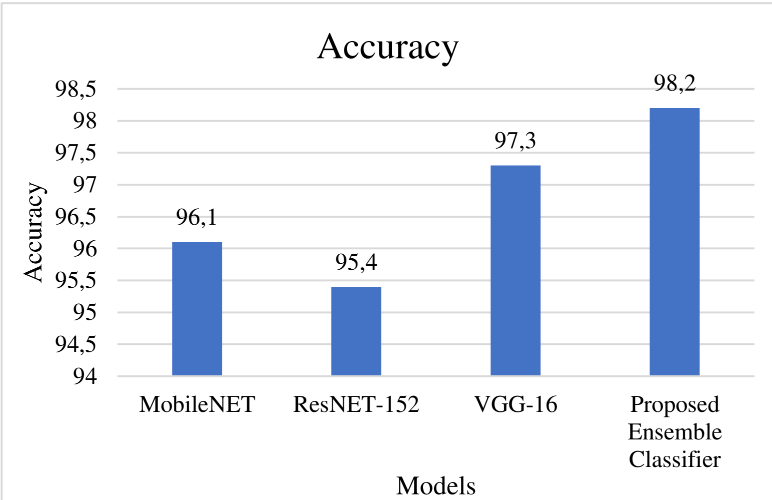
ResNet-152

ResNet-152, part of the Residual Networks family, is known for its deep architecture, comprising 152 layers. It addresses the vanishing gradient problem through the use of residual connections, which allow gradients to propagate through the network more effectively. This deep structure enables ResNet-152 to learn intricate features from complex data, such as MRI images. In our study, ResNet-152 achieved a notable accuracy of 97.71% on the testing data. This high accuracy reflects its ability to handle the complexities and nuances in the MRI images, making it a reliable model for detailed and accurate brain tumor classification.

VGG-16

VGG-16 is a deep convolutional neural network with 16 layers, known for its simplicity and effectiveness in image classification tasks. It uses small 3x3 convolution filters, which increases the depth of the network while maintaining manageable computational complexity. In the classification of brain tumors, VGG-16 demonstrated an impressive accuracy of 98.62% on unseen MRI images. This high performance is attributed to its robust feature extraction capabilities, which allow it to distinguish between different tumor types with high precision. VGG-16's success in this context highlights its reliability and efficiency in medical image analysis.

Figure 2: Comparative Analysis of Model Performance on Brain Tumor Classification



Proposed Ensemble Classifier

The proposed ensemble classifier leverages the strengths of multiple robust models to enhance the accuracy and reliability of brain tumor classification. By combining the outputs of the Custom CNN, MobileNet, ResNet-152, VGG-16, and DenseNet-169 models, the ensemble approach aims to mitigate the weaknesses of individual models and capitalize on their strengths. Each model processes the MRI images independently, and their predictions are aggregated to provide a final classification. This ensemble strategy not only boosts the overall accuracy but also offers significant reliability in predicting the presence and type of tumor. The detailed comparison and analysis of each model's output, as shown in Figure 2, demonstrate the efficacy of this approach. The ensemble classifier ensures that the final prediction is more robust and less prone to errors, providing a comprehensive solution for brain tumor detection and classification.

Conclusion

In conclusion, this research provides a comprehensive solution for brain tumor classification using MRI images through the application of advanced deep learning models. By employing a combination of a custom CNN architecture and state-of-the-art transfer learning models such as MobileNet, ResNet-152, VGG-16, and DenseNet-169, the proposed system achieves high accuracy and robustness in detecting and categorizing brain tumors. The use of these models, along with extensive preprocessing and data augmentation techniques, ensures that the system is capable of accurately predicting the presence and type of tumor, even in previously unseen images. The results indicate that the proposed ensemble classifier approach significantly enhances diagnostic precision, with individual models showing accuracies as high as 98.63%. The comparative analysis of the five robust models highlights their respective strengths and effectiveness in different scenarios, offering valuable insights for future research and clinical applications. The study demonstrates that integrating multiple deep learning techniques can provide a more reliable and comprehensive diagnostic tool. This approach not only improves the accuracy of tumor detection but also offers a scalable solution that can be expanded to include additional tumor types and imaging data. Overall, the findings underscore the potential of deep learning in transforming medical imaging and diagnostics, paving the way for more precise and efficient healthcare solutions.

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