Brain Tumor Classification using Transfer Learning and Ensemble Approach

Jishan Shaikh[1], Kaina Shaikh[2]

[1]Department of Computer Engineering, VPKBIET, Savitribai Phule Pune University, Baramati, India

[2]Department of Artificial Intelligence & Data Science, VPKBIET, Savitribai Phule Pune University, Baramati, India

E-mail: [1]jishanshaikh1004@gmail.com, [2]kainashaikh@gmail.com

Abstract

Precise brain tumor classification is essential for efficient diagnosis and treatment planning in the field of medical image analysis. This study investigates hybrid models integrating transfer learning with ensemble methods to enhance classification accuracy. Specifically, the combinations of EfficientNetB3 and VGG19 as feature extractors coupled with Random Forest classifiers. The findings demonstrate significant performance improvements over standalone deep learning approaches. The EfficientNetB3 + Random Forest ensemble achieves an accuracy of 89%, while the VGG19 + Random Forest ensemble achieves 93%, outperforming the KNN+SVM hybrid model. These results highlight the efficacy of using transfer learning for feature extraction and ensemble methods for decision fusion in medical image classification tasks. Moreover, the study contributes insights into optimizing model performance through hyperparameter tuning and data augmentation, essential for enhancing robustness and generalizability across diverse MRI datasets. This research advances the understanding and application of hybrid models in medical imaging, with implications for improving diagnostic accuracy and clinical decision-making.

Keywords: Random Forest Classifier, VGG19, EfficientNetB3, Ensemble Learning, Transfer Learning.

DOI: https://doi.org/10.36548/jscp.2024.3.005
Received: 13.07.2024, received in revised form: 03.08.2024, accepted: 14.08.2024, published: 22.08.2024

1. Introduction

Brain tumors are among the most difficult challenges in medical diagnostics and treatment due to their complex nature and high variability. Determining the best course of treatment and enhancing patient outcomes depend on the quick and accurate classification of brain tumors. Time-consuming and error-prone, traditional diagnostic techniques mostly involve radiologists manually evaluating medical images. In recent years, the combination of artificial intelligence (AI) and deep learning techniques has shown great promise for automating and improving the accuracy of brain tumor classification [6].

Early detection is essential for the successful treatment of brain tumors [9]. The development of medical imaging techniques has allowed doctors to see the structure of the human brain clearly, which is beneficial for treating and diagnosing brain cancers. Transfer learning, a powerful deep learning technique, involves using pre-trained models on large datasets and fine-tuning them for specific tasks with limited data availability. Deep learning, a subset of machine learning, employs artificial neural networks with multiple layers to learn and extract features from raw data. This approach is very useful in medical imaging, where acquiring labelled data is often difficult. Using pre-trained models, researchers can achieve great performance with relatively minimal datasets, solving one of the major limits of deep learning in the medical domain [11-13].

In this work, the performance of two hybrid models is examined for the classification of brain cancers from MRI images, which incorporate ensemble techniques and transfer learning. In the first hybrid model, a Random Forest classifier (VGG19+RF) is integrated with the VGG19 architecture for feature extraction. The second hybrid model uses a Random Forest classifier (EfficientNetB3+RF) after extracting features using the EfficientNetB3 architecture. The rich characteristics acquired from brain MRI scans are used by both models through transfer learning and subsequently classified using Random Forest, an ensemble learning technique renowned for its excellent performance and resilience.

Pre-trained on the ImageNet dataset, the VGG19 model, notable for its deep architecture, achieves better performance at extracting fine-grained features from images. Another architecture, EfficientNetB3, performs exceptionally well with less processing power and parameters thanks to its compound scaling technique, which scales the network's depth, width, and resolution equally. The combination of these pre-trained models with Random

Forest classifiers aims to utilize the strengths of both deep learning and ensemble learning techniques.

2. Related Work

A hybrid CNN model with two and three path networks was developed by Sajid et al. [1] for improved brain tumor detection in BRATS MR images. The model has 91% specificity, 86% sensitivity, and 86% dice. The suggested strategy in [2] enhances MRI quality by normalization, densely accelerated features, and gradient approaches. Tested on a large dataset, it outperformed conventional approaches by 90%.

Shaveta and Meghna conducted an exploratory analysis of brain MRI images for brain tumor classification and compared various CNN-based transfer learning models to identify different types of brain tumors [3]. To improve the segmentation, and classification of brain diagnoses for precise detection and classification of brain cancers, they employed techniques, such as computer vision, pattern analysis, and medical image processing [4]. Pareek et al. [5] developed a method that uses kernel support vector machines (KSVM) to detect and classify brain malignancies. Their method achieved an accuracy of 97% in classifying brain tumors using 150 T1-weighted MRI brain images.

Meenakshi and Revathy created a deep learning model that uses a back propagation neural network classifier to predict brain stroke from CT/MRI scan images. High sensitivity, specificity, precision, and accuracy are produced by the proposed model, whose efficacy and accuracy are evaluated and compared with those of existing models [7].

Two pre-trained convolutional neural network (CNN) models, VGG16 and VGG19, were utilized to extract features through transfer learning. In the third step, an extreme learning machine (ELM) and a combined learning approach based on cross-entropy were used to identify the best features. In the fourth step, robust covariant features, derived using partial least squares (PLS) were combined into a single matrix. The accuracy values achieved on the BraTS datasets were 97.8% for BraTS2015, 96.9% for BraTS2017, and 92.5% for BraTS2018, demonstrating the effectiveness of the proposed approach [10].

3. Proposed Work

3.1 Dataset

The dataset used in this work is a comprehensive compilation drawn from three sources: figshare [15], the SARTAJ dataset [16], and Br35H [17]. It includes a total of 7,023 MRI scans of the human brain, which have been classified into four categories: pituitary, glioma, meningioma, and no tumor, as detailed in Table 1. However, there are discrepancies in the reported figures that could not be fully accounted for. The 'no tumor' images were sourced from the Br35H dataset. Figure 1 shows the different types of brain tumor images used for this research.

Table 1. Number of Images for Each Class

Class	Number of images
Pituitary	1457
Glioma	1321
Meningioma	1339
No Tumor	1595

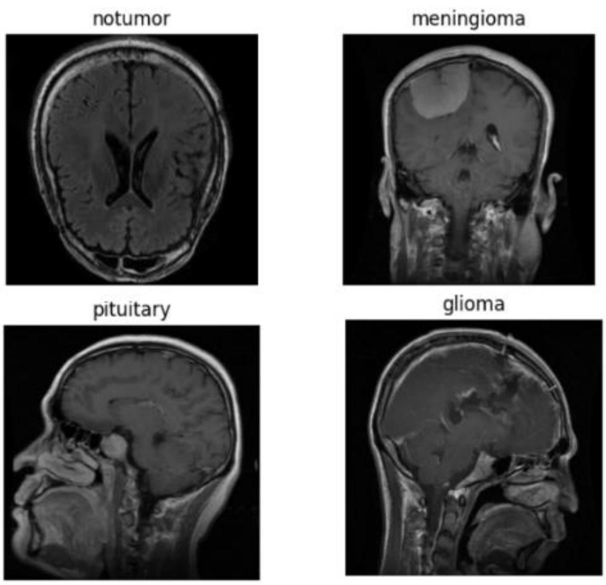

Figure 1. Types of Brain Tumour in Dataset

3.2 Proposed Method

This section describes the two hybrid models (VGG19+Random Forest and EfficientNetB3+Random Forest) that have been suggested for brain tumor classification. Each model uses a Random Forest classifier for classification after extracting features from MRI images through the use of transfer learning. By combining the benefits of ensemble learning with deep learning, the method depicted in Figure 2 improves the precision and resilience of brain tumor diagnosis.

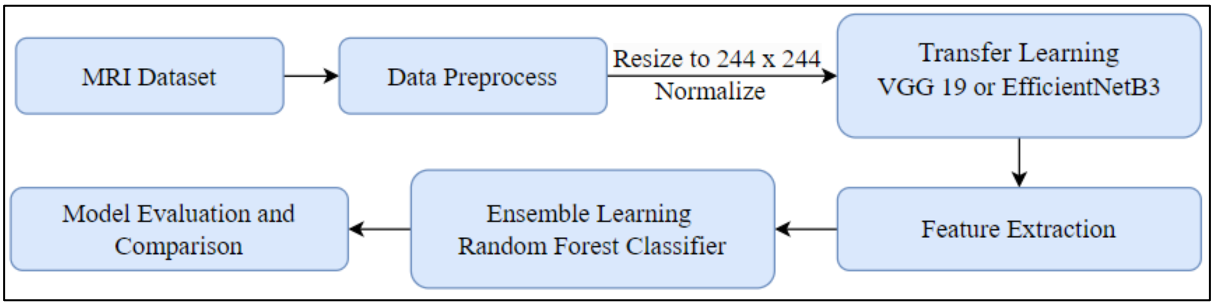

Figure 2. Flow of Proposed Approach

The capacity to extract significant and high-level information from medical images is essential for precise tumor classification. VGG19's sequential convolutional layers effectively capture the hierarchical characteristics, whereas EfficientNetB3 balances network depth and width to give robust feature extraction capabilities that generalize well across different types of brain tumors. Both models are pretrained on the ImageNet dataset, which serves as a solid foundation for transfer learning, resulting in faster convergence and improved performance when fine-tuned on a smaller, domain-specific dataset such as brain tumor MRI images. The use of ensemble approaches, such as transfer learning and Random Forest classifiers, improves classification accuracy and robustness. The models were implemented and trained on Google Colab using a T4 GPU, utilizing its computational capabilities for efficient processing and training.

Table 2. Illustration of Proposed Architecture with Number of Layers and Modifications

Model	Layer Type	Number of Layers	Number of Parameters	Modifications
VGG19 + RF	Convolutional	16	20,024,064	Top fully connected layers removed. Output from second-last convolutional layer used as feature vector.
	Max Pooling	5	-	None
	Fully Connected (Dense)	3	-	None
	Random Forest	-	350 estimators	Feature vectors fed into RF classifier
EfficientNetB3+ RF	Convolutional	24	12,233,232	Top fully connected layers removed. Output from global average pooling layer used as feature vector.
	Global Average Pooling	1	-	None
	Fully Connected (Dense)	1	-	None
	Random Forest	-	350 estimators	Feature vectors fed into RF classifier

Random Forest classifiers are well-known for their capacity to handle multidimensional feature spaces and their resistance to overfitting. The suggested models achieve better classification accuracy and generalization performance by fusing the diverse feature representations derived by VGG19 and EfficientNetB3 with Random Forest's ensemble learning capabilities. The Table 2 illustrates architecture of both proposed models in detail and also highlights the modifications done in this study.

3.2.1 VGG19 with Random Forest

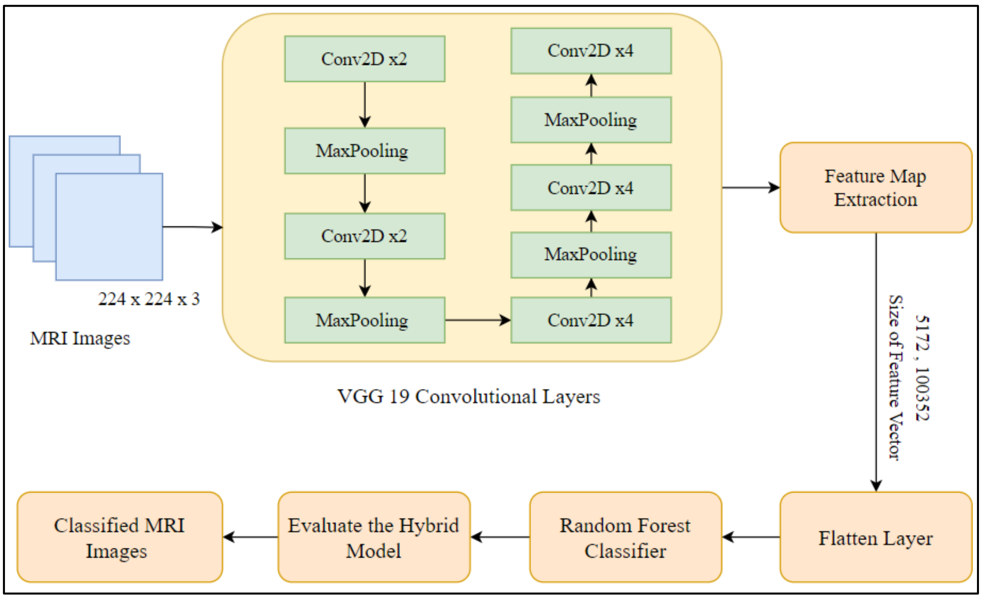

Figure 3. Proposed Hybrid System (VGG19+ RF) Architecture

The VGG19 architecture, shown in Figure 3, is a convolutional neural network (CNN) known for its depth and ability to extract complex features from images, the proposed hybrid system combines VGG19+Random Forest model. The ImageNet dataset, which has millions of annotated photos in thousands of categories, is used to pre-train the VGG19 model. The VGG19 architecture includes five sets of feature extraction layers followed by max-pooling layers. When an image with dimensions of 224 by 224 pixels is input into the model, it returns the corresponding label[8]. The study uses a pre-trained VGG-19 model for feature extraction with Random Forest applied for classification. The pretraining allows the model to develop rich and generalizable features, which are then utilized in the task of classifying brain tumors.

Brain MRI scans are processed to extract features using the pre-trained VGG19 model. Through the use of its convolutional layers, the model processes the images and captures different levels of detail and abstraction [8]. The feature representation of the images is the output of the second-last convolutional layer, which captures high-level features important for the classification task.

The extracted features are fed into a Random Forest classifier. The ensemble learning method constructs multiple decision trees during training and uses their collective predictions to determine the class mode for classification. The ensemble approach of Random Forest enhances the model accuracy by improving robustness and reducing the risk of overfitting. The model classifies MRI scans into four categories of brain tumours: glioma, meningioma, pituitary tumour, and no tumour. The deep features extracted by VGG19 captures the distinctive characteristics of each tumor type, which the Random Forest classifier for accurate classification.

3.2.2 EfficientNetB3 with Random Forest

Utilizing the EfficientNetB3 architecture, which is optimized for high performance with fewer parameters and computing resources, the EfficientNetB3+Random Forest model is illustrated in Figure 4. EfficientNetB3 achieves high accuracy by balancing network depth, breadth, and resolution through compound scaling thereby maintaining efficiency . The EfficientNetB3 model employed for feature extraction, is previously been trained on the ImageNet dataset. Its scaled convolutional layers effectively capture both detailed and high-level characteristics. The output from EfficientNetB3's final pooling layer is used as the feature representation for classification.

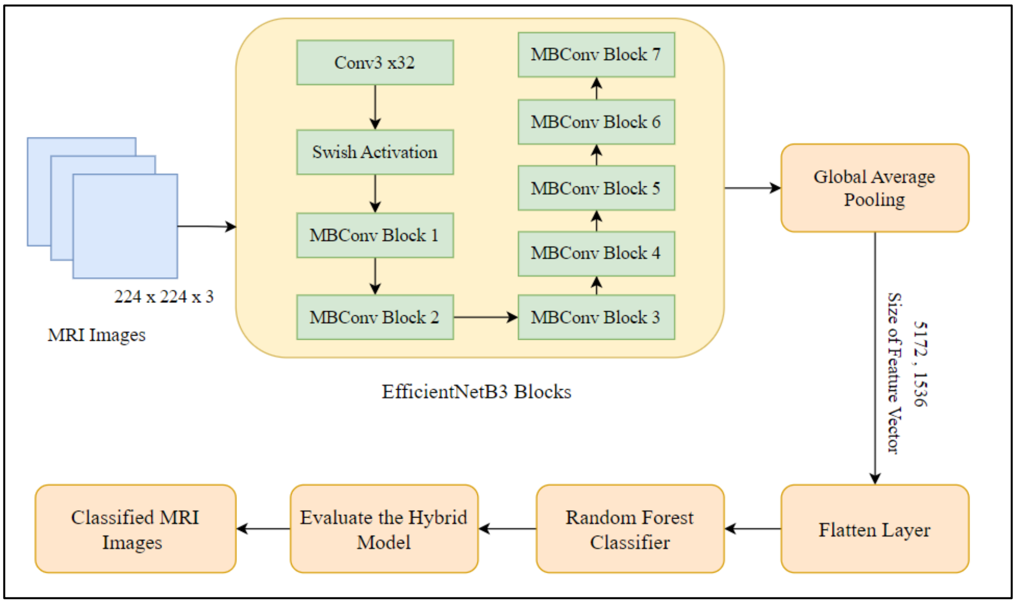

Figure 4. Proposed Hybrid System (EfficientNetB3 + RF) Architecture

The extracted features are fed into a Random Forest classifier. This classifier classifies the brain tumor types by gathering the predictions of multiple decision trees, resulting in robust and accurate classification. This ensemble strategy improves the model's generalizability while reducing the impact of noisy or irrelevant features. Similar to the VGG19+RF model, the EfficientNetB3+RF model classifies MRI images into four brain tumor categories. The efficient and detailed feature extraction by EfficientNetB3, combined with Random Forest's ensemble learning, ensures precise classification of glioma, meningioma, pituitary tumor, and no tumor images.

4. Results and Discussion

4.1 Proposed Method Results

In this section, the performance of the two proposed hybrid models: VGG19+Random Forest and EfficientNetB3+Random Forest are presented. The models were evaluated on a dataset of brain MRI images categorized into four types: glioma, meningioma, pituitary tumor, and no tumor. The key metrics used for evaluation were accuracy, precision, recall, and F1-score. The VGG19+Random Forest model demonstrated an impressive performance with a training accuracy of 100% and a test accuracy ranging between 93%. The model achieved high precision, recall, and F1-score across all tumor categories, as shown in Figure 5. Specifically, in the training set, the model attained an average precision of 98.5%, recall of 98.3%, and F1-score of 98.4%. The Figure 5 represents the confusion matrix of VGG19 and Random Forest Model, where the numbers 0,1,2, and 3 on axis represents the classes.

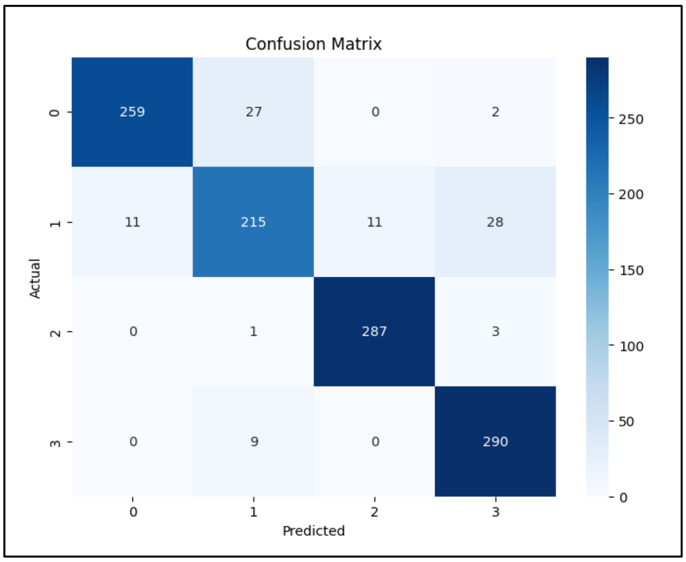

Figure 5. Confusion Matrix of VGG19 + Random Forest Model

The classes are named accordingly, 0: glomia, 1: meningioma, 2: No tumour and 3: pituitary respectively. These metrics indicate that the model is highly effective at correctly identifying and classifying the different types of brain tumors with minimal misclassifications.

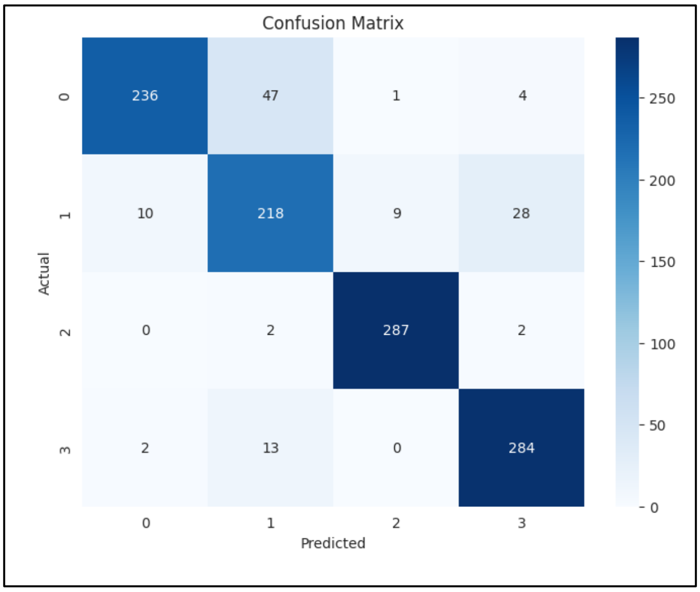

Figure 6. Confusion Matrix of EfficientNetB3 + Random Forest Model

The EfficientNetB3+Random Forest model, on the other hand, also performed robustly but with slightly lower accuracy compared to the VGG19+Random Forest model. It achieved a training accuracy of 93.5% and a test accuracy of 89%. Despite the marginally lower accuracy, the EfficientNetB3+Random Forest model maintained high precision, recall, and F1-scores, as shown in Figure 6, reflecting its capability to accurately classify brain tumor types. The lower test accuracy suggests that, while EfficientNetB3 is efficient in feature extraction, it might not generalize as well as the VGG19-based model in this specific context. The confusion matrix of VGG19 + RF model shows better result compared to the confusion matrix of EfficientNetB3 + RF.

The t-SNE plots in Figure 7 provides a graphical representation of the features extracted using VGG19 and EfficientNetB3. Each point in the scatter plots represents an image from the dataset, projected on two dimensions for visualization purposes. The t-SNE (t-Distributed Stochastic Neighbour Embedding) plot for VGG19 features shows a densely packed distribution of data points. This indicates that VGG19 extracts a wide variety of features, capturing the intricate details of the input images. The dense clustering may suggest that VGG19 effectively differentiates between various patterns present in the brain MRI images. The t-SNE plot for EfficientNetB3 features also shows a densely packed distribution but with a different spread compared to VGG19. EfficientNetB3 uses a compound scaling method, which may result in different feature representation characteristics. The spread of points indicates the model's efficiency in capturing diverse and discriminative features from the images. These visualizations help in understanding the feature extraction capabilities of both models and how they represent the data in a lower-dimensional space.

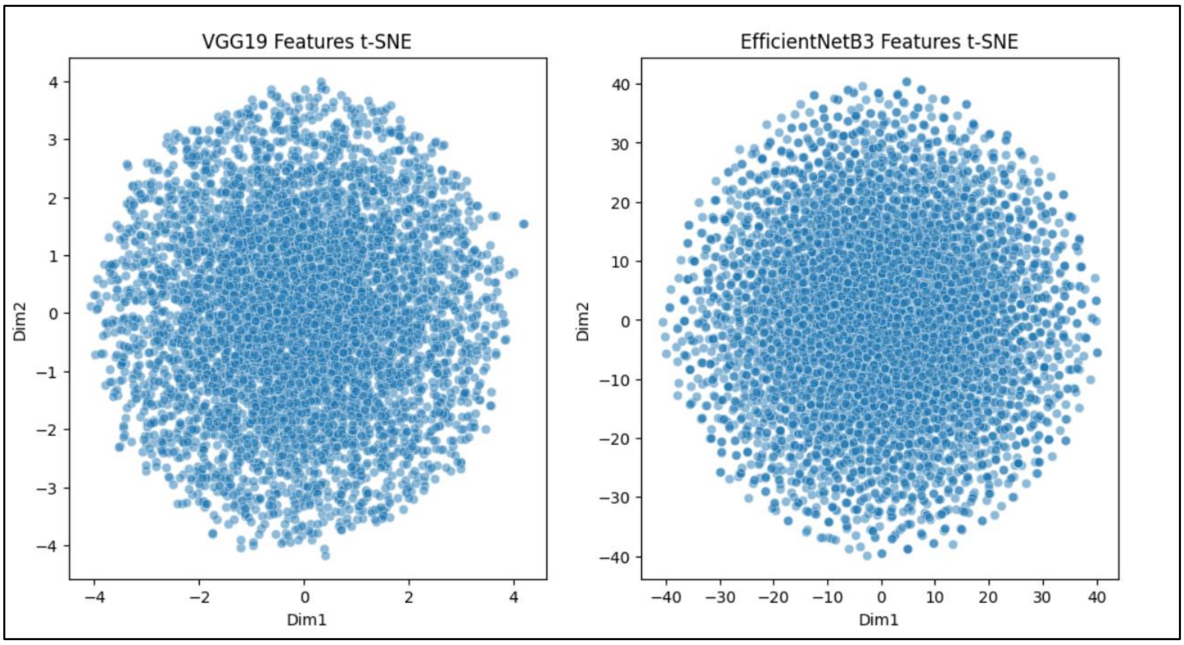

Figure 7. Feature Visualization of VGG19 and EfficientNetB3

4.2 Accuracy

The VGG19+Random Forest model achieved higher test accuracy (93%) compared to the EfficientNetB3+Random Forest model (89%). This suggests that the feature extraction capabilities of VGG19, when combined with the robust classification abilities of Random Forest, lead to better generalization and classification accuracy on the test dataset. The EfficientNetB3 architecture is designed to balance network depth, width, and resolution, making it efficient in terms of computational resources. However, the VGG19 model, despite being less efficient computationally, appears to extract more relevant features for this specific task, leading to higher classification accuracy. The Table 3 describes the performance metric of both the proposed model. The main goal of the study was to demonstrate the result by comparing models with existing hybrid model. The Table 4 depicts the comparison of accuracy between existing hybrid model SVM+ KNN [14] and proposed hybrid model with ensemble learning method.

Table 3. Performance Metric for VGG19 + Random Forest

Metric	VGG19 + RF	EfficientNetB3+ RF
Accuracy	92-93	89
Precision	98.5	89.8
Recall	98.3	88.5
F1-score	98.4	89.5

Table 4. Comparison with Existing Hybrid Model

Model	Accuracy
VGG19 + RF	93%
EfficientNetB3 + RF	89%
SVM + KNN [14]	91.2%

5. Conclusion

In this research, two hybrid models were proposed for brain tumor classification: VGG19 combined with Random Forest (VGG19+RF) and EfficientNetB3 combined with Random Forest (EfficientNetB3+RF). The selection of these transfer learning models was based on their proven performance on benchmark datasets, model complexity, feature extraction capabilities, transfer learning efficiency, and scalability. VGG19+RF achieved an accuracy of 92-93%, while EfficientNetB3+RF attained an accuracy of 89%. A detailed analysis revealed that the VGG19+RF model outperformed existing hybrid models such as KNN+SVM, demonstrating superior precision, recall, and F1 scores. While other advanced models like ResNet50, GoogLeNet, AlexNet, and VGG16 have shown better results in the literature, the primary objective was to compare the performance of the proposed hybrid models with existing hybrid approaches. The findings confirm that the combination of VGG19 and Random Forest is more effective than KNN+SVM for this specific task.

Looking forward, various areas for improvement and future research are identified. Expanding the dataset to include more diverse MRI images from various demographics and imaging settings may improve model robustness and generalizability. Advanced data augmentation strategies and hyperparameter tuning could enhance model performance while reducing overfitting. Future work will focus on exploring other advanced deep learning architectures and ensemble methods to further enhance classification accuracy. Additionally, integrating more comprehensive preprocessing steps and expanding the dataset to include more diverse tumor types could improve the model's generalizability and robustness. Despite the promising results, limitations such as computational resource requirements and the need for extensive hyperparameter tuning remain. Addressing these challenges will be essential for the practical deployment of these models in clinical settings.

References

[1] Sajid, Sidra, Saddam Hussain, and Amna Sarwar. "Brain tumor detection and segmentation in MR images using deep learning." Arabian Journal for Science and Engineering 44 (2019): 9249-9261.

[2] Ayadi, Wadhah, Imen Charfi, Wajdi Elhamzi, and Mohamed Atri. "Brain tumor classification based on hybrid approach." The Visual Computer 38, no. 1 (2022): 107-117.

[3] Arora, S., and M. Sharma. "Deep Learning for Brain Tumor Classification from MRI Images." In Proceedings of the Sixth International Conference on Image Information Processing (ICIIP), Shimla, India, 26–28 November 2021, 409–412.

[4] Kibriya, H., M. Masood, M. Nawaz, R. Rafique, and S. Rehman. "Multiclass Brain Tumor Classification Using Convolutional Neural Network and Support Vector Machine." In Proceedings of the Mohammad Ali Jinnah University International Conference on Computing (MAJICC), Karachi, Pakistan, IEEE, 2021, 1–4.

[5] Pareek, Meenakshi, C. K. Jha, and Saurabh Mukherjee. "Brain tumor classification from MRI images and calculation of tumor area." In Soft Computing: Theories and Applications: Proceedings of SoCTA 2018, Singapore: Springer Singapore, 2020. 73-83.

[6] Borole, Vipin Y., Sunil S. Nimbhore, and Dr Seema S. Kawthekar. "Image processing techniques for brain tumor detection: A review." International Journal of Emerging Trends & Technology in Computer Science (IJETTCS) 4, no. 5 (2015): 2.

[7] Meenakshi, A., and S. Revathy. "An Efficient Model for Predicting Brain Tumor Using Deep Learning Techniques." In Proceedings of the 5th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, IEEE, 2020, 1000–1007.

[8] El Kaitouni, S.E.I., and H. Tairi. "Segmentation of Medical Images for the Extraction of Brain Tumors: A Comparative Study Between the Hidden Markov and Deep Learning Approaches." In Proceedings of the International Conference on Intelligent Systems and Computer Vision (ISCV), Fez, Morocco, IEEE 2020, 1–5.

[9] Ali, M., J.H. Shah, M.A. Khan, M. Alhaisoni, U. Tariq, T. Akram, Y.J. Kim, and B. Chang. "Brain Tumor Detection and Classification Using PSO and Convolutional Neural Network." Computers, Materials & Continua 73 (2022): 4501–4518.

[10] Khan, M.A., I. Ashraf, M. Alhaisoni, R. Damaševičius, R. Scherer, A. Rehman, and S.A.C. Bukhari. "Multimodal Brain Tumor Classification Using Deep Learning and Robust Feature Selection: A Machine Learning Application for Radiologists." Diagnostics 10 no. 8 (2020): 565.

[11] Mahmoud, Amena, Nancy Awadallah Awad, Najah Alsubaie, Syed Immamul Ansarullah, Mohammed S. Alqahtani, Mohamed Abbas, Mohammed Usman, Ben Othman Soufiene, and Abeer Saber. "Advanced Deep Learning Approaches for Accurate Brain Tumor Classification in Medical Imaging." Symmetry 15, no. 3 (2023): 571. https://doi.org/10.3390/sym15030571.

[12] Swati, Zar Nawab Khan, et al. "Brain Tumor Classification for MR Images Using Transfer Learning and Fine-Tuning." Computerized Medical Imaging and Graphics 75 (2019): 34–46.

[13] Pundir, Aaditya, and Er Rajeev Kumar. "Brain tumor classification in MRI images using transfer learning." Machine Learning for Intelligent Multimedia Analytics: Techniques and Applications (2021): 307-319.

[14] Cheng, Jun, Wei Huang, Shuangliang Cao, Ru Yang, Wei Yang, Zhaoqiang Yun, Zhijian Wang, and Qianjin Feng. "Enhanced performance of brain tumor classification via tumor region augmentation and partition." PloS one 10, no. 10 (2015): e0140381.

[15] https://www.kaggle.com/datasets/mdkhurshidjahan01/figshare-brain-tumor-dataset/discussion?sort=undefined

[16] https://www.kaggle.com/sartajbhuvaji/datasets.

[17] https://www.kaggle.com/datasets/ahmedhamada0/brain-tumor-detection

Author's biography

Jishan Shaikh received his B.E. degree in Computer Engineering from Savitribai Phule Pune University, Maharashtra, India, in 2024. He has conducted research in the fields of Computer Vision and Natural Language Processing. His research interests encompass Computer Vision, AI, Robotics, and NLP.

Kaina Shaikh received her B.E. degree in Artificial Intelligence and Data Science from Savitribai Phule Pune University, Maharashtra, India, in 2024. She has conducted research in the fields of Deep Learning, Machine Learning and Quantum Machine Learning. Her research interests encompass Computer Vision, AI, ML and NLP.