Hybrid Deep Feature Fusion with PCA–mRMR Optimization for Multi-Class Brain Tumor Classification from MRI Images

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Abstract

Classifying brain tumors from MRI scans is really tough because of all the noise and variation in the images and some tumors can look pretty similar. Even though deep learning models do a job they can miss important details if they are working alone and combining models can lead to repeating information. This research suggests using a combination of ResNet50 and VGG16 to get a look at the features of the tumors and then using PCA and mRMR to pick the most important ones. The goal is to tell apart four types of tumors which're glioma, meningioma, pituitary and no tumor using a multi-class SVM. This approach works well getting it right about 94.51 percent of the time. The good news is that it still works almost as well at 94.39 percent even when it is optimized to use fewer features and run faster which makes it a great tool, for helping doctors make decisions quickly and efficiently.

Keywords

Feature Fusion combines features, ResNet50 and VGG16 are deep learning models, PCA, mRMR help in Feature Selection, Support Vector Machine.

1. Introduction

Brain tumors are a problem for our health. They happen when cells in the brain grow in a way and can really affect how our brain works. We need to find brain tumors and make sure we know what is going on so we can help people get better. According to what doctors are saying about health around the world finding brain tumors early is very important for helping people survive and for making a good plan to treat them. Doctors like to use Magnetic Resonance Imaging, which is called MRI for short to look at the brain because it's very good, at showing what is going on inside our brain. MRI is also good because it does not hurt and we do not have to cut into the brain to use it. The problem is that when doctors look at the MRI pictures it takes a time and they might not always agree on what they see. This can be very hard to deal with when we are talking about a lot of people who need help [1].

To fix these problems people are using computer programs to help doctors diagnose diseases. These programs are called computer-aided diagnosis systems. The old way of doing things used machine learning, which relied on people to decide what features to look for like the intensity and shape of tumors.. This old way often did not work well because it could not capture all the complex things about tumors [2]. In the few years new techniques called deep learning have been used, especially something called Convolutional Neural Networks. These Convolutional Neural Networks have been very good, at analyzing images by teaching themselves what to look for in the images. This is an improvement because the computer can learn from the images directly without people having to tell it what to look for [1].

When we look at CNN architectures we see that ResNet50 and VGG16 are really good at getting features from data. ResNet50 uses something called learning to deal with the problem of vanishing gradients, which means it can train deeper networks and get features that are more meaningful. This is because ResNet50 can capture level semantic features [4]. On the hand VGG16 has a simple architecture with small filters that are good at getting details that are very fine and structural. Even though ResNet50 and VGG16 are both good using one of them may not be the best idea because they can only get a limited number of features [5]. To make this better some people have tried combining features from deep networks to make them work better together. This is called feature fusion.For example features from ResNet50. Vgg16 can be combined [6]. However when we do this we often end up with a lot of features that're not useful and take up a lot of space which can make it harder to classify things and use more computer power. So we need to be careful when we combine features, from ResNet50 and VGG16.

We need to deal with this problem by using dimensionality reduction and feature selection techniques. One way to do this is with Principal Component Analysis, which is often used to change dimensional data into a lower-dimensional space while keeping as much variation as possible. However Principal Component Analysis does not directly think about how features and class labelsre related [7]. To pick the features we can use Minimum Redundancy Maximum Relevance, which is a good method for selecting features that are useful for target classes and not too similar, to each other. Minimum Redundancy Maximum Relevance uses information to balance how relevant features are to target classes and how redundant they are [8].

This paper is based on some things we found out. We are suggesting a way to combine features from pictures using deep learning. This new way uses ResNet50. Vgg16 to get good features from the pictures. Then we use something called PCA to rank these features and mRMR to pick the ones. Our goal is to make a system that can tell what kind of brain tumor someone has. We want to be able to tell if someone has Glioma, Meningioma, Pituitary or if they do not have a tumor all. By putting together features from sources and using good methods to optimize them we can make our system better and faster. The main things we did in this work are:

- We made a deep learning system that uses both ResNet50 and VGG16 to get lots of features from pictures.
- We found a way to combine these features so they work well together.
- We used PCA to make the features smaller and mRMR to pick the features.
- We made a system that's better, at telling what kind of brain tumor someone has when looking at MRI pictures of their brain.

2. Literature Review

Brain tumor classification research using MRIs include techniques that integrate new learning techniques. MRI data contains brain tumor types that are challenging to discriminate. The majority of these techniques employs PCA as the primary tool to lessen the dimensions of the MRI data available. For example, data from MRI tumor scans shows that PCA retained 88.98% of the MRI data variance. This means that the accuracy remained below 95% which means that PCA by itself has proven insufficient in differentiating brain tumor types within an MRI data. The low accuracy has prompted some researchers to combine PCA with some other techniques. For example, the combination of PCA, some features, and a peculiar classifier called RELM, attained 94.23% accuracy which is an improvement to the use of old features alone. MRI brain tumor classification ones that use a combination of learning and traditional machine learning are no exception. A learning model combined with a support vector machine yielded an overall accuracy of 96%. However, the accuracy of tumor types classification fell below 95% for some types. This can be attributed to the existence of more visible features, and therefore, the model did not generalize well. In addition to these, traditional methods that combine features with learning are also known to employ PCA and/or techniques. In some tumor grades, they report the accuracies of less than 95%. This suggests that they are prone to the inconsistencies in imaging data and protocol quality. In spite of the advancements in artificial intelligence and machine learning, MRI encompasses the dilemmas that MRI classification processes face. Classifying brain tumors is still a challenge [12].

Improving things is the job of some researchers. However, they also encounter challenges. For example, MRI image classification using the R-CNN model combined with L1NSR-based feature selection method yielded relatively good results, but the model struggled with lesion classification. This exemplifies the challenges that arise when there is a wide variety of categories to classify, such as brain tumors. Some people have also tried using learning models that combine machine learning classifiers. However the accuracy of these MRI-based brain tumor classification models varies a lot depending on the type of image the conditions and the dataset used. Often the accuracy of these MRI-based brain tumor classification models is below 95 percent, which means these MRI-based brain tumor classification models are not robust enough. Explain ability-driven architectures have their performance issues. Hybrid transfer-learning methods that combine feature fusion with model explain ability, such as SHAP and Grad-CAM provide understanding of the results of MRI-based brain tumor classification models. However these methods are complex. Have limitations, which affect the accuracy of MRI-based brain tumor classification models for certain tumor categories resulting in some class-level results below 95%. These studies collectively show that MRI-based brain tumor classification models have performance issues, with tumor types. MRI-based brain tumor classification models struggle with tumor types that look similar. Brain tumor classification remains a task. The accuracy of brain tumor classification models MRI-based brain tumor classification models varies a lot. Brain tumor classification models, including MRI-based brain tumor classification models have performance issues.

- Redundancy in feature spaces
- Variability across different MRI scanners
- Poorly optimized feature selection

PCA reduces the number of features, and techniques like L1NSR highlight the more useful ones. But honestly, neither method captures enough of the data's variation or picks the right features to make a real impact on tumor classification. So, we need something more powerful to get better accuracy. The real aim is to build a system that can consistently tell different tumor types apart. That's where transfer learning and merging features really matter. It's also crucial to make the model's decisions easy to understand—tools like SHAP and Grad-CAM help with that, building trust in the results. When you bring all these ideas together, you get a system that does a much better job at classifying tumors. The classification system helps in identifying tumor classes Classification results improve with a hybrid framework. This framework helps in achieving classification, across tumor classes.

Table 1: Literature Review

Citation	Study	Methodology	Feature Optimization	Reported Performance
9	PCA MRI Analysis	PCA for variance reduction in MRI tumor features	PCA	<95% accuracy despite 88.98% variance retention
10	PCA-NGIST + RELM	NGIST handcrafted features + PCA + RELM classifier	PCA	94.23% accuracy
13	Hybrid CNN–SVM	CNN feature extraction + SVM classification	None	Per-class performance <95%
12	Radiomic–Deep Fusion	Hybrid radiomics + DL across multicenter data	PCA + radiomic selection	Some tumor grades <95%
11	R-CNN + L1NSR Selection	Region-based CNN with L1NSR feature filtering	L1NSR	Class-wise performance <95%
14	Hybrid TL + Explainability	TL backbone + multiscale fusion + SHAP	Various (fusion + explainability)	Underperforming categories <95%
15	Deep+ML Combined Classifier	CNN feature extractor + ML classifiers	None	Sub-95% performance across conditions

The brain tumor classification models that use MRI scans are not accurate enough. This is because they do not choose the features. PCA is a method that reduces the amount of data. It does not show the complicated relationships between things so it does not separate tumors well. Other models, like hybrid and deep learning models that use SVM and radiomics also have trouble choosing the features and working with different types of images. Brain tumor classification models need ways to choose features so they can classify tumors correctly. The current models are not good enough so we need to find effective methods to improve them. Brain tumor classification models that use MRI scans need to get better at choosing features [9]-[12].

Despite methods like mRMR being available no studies with less than 95% accuracy use a two-stage PCA and mRMR optimization process. This process helps to keep the information and remove similar features. As a result current hybrid models have limitations, they struggle to balance keeping the characteristics and selecting the most relevant features. A research gap exists in creating a model that combines feature fusion with a PCA and mRMR optimization process. The goal of this model is to improve performance stability across MRI tumor datasets. It also aims to address the issue of discriminability in models with moderate accuracy. The mRMR method is key here as it helps in selecting the relevant features. Current models do not utilize mRMR and PCA effectively. Therefore a new approach that incorporates both PCA and mRMR is needed. This will help in achieving results, in MRI tumor classification.

Motivation

Classifying brain tumors from MRI scans is really tough. There is a lot of variability and noise in the scans and the boundaries are not always clear. This can make it hard to diagnose the tumors correctly. The models we have now do not work well because we do not have enough data. It is also hard for these models to understand the patterns in the scans. Sometimes they even look at things that're not important. Combining features can make the models work better..

It can also make them look at the same things too many times. The ways we choose which features to look at are not very good either. We need a model that is really good at choosing the important features and combining them in a smart way. This will make the diagnoses more accurate. Help doctors make consistent decisions, about brain tumors from MRI scans.

3 Proposed Framework

The new system combines good ways to look at details mix different kinds of details together and pick the best details to tell brain tumor MRI images apart. It puts these images into four groups: Glioma, Meningioma, Pituitary and No Tumor. The whole process has four steps:

1. Deep feature extraction using ResNet50 and VGG16
2. Hybrid feature fusion
3. Feature ranking and dimensionality reduction using PCA
4. Optimal feature selection using mRMR
5. Final classification

Let the input MRI dataset be defined as:

$$\mathrm{D} = \{(x_i, y_i)\}_{i=1}^{N}$$

where $x_i$represents the MRI image and $y_i \in \{C_1, C_2, C_3, C_4\}$denotes the class labels corresponding to Glioma, Meningioma, Pituitary, and No Tumor.

3.1 Dataset

The Brain Tumor MRI dataset used in this study is a publicly available collection from Kag-gle, compiled by Masoud Nickparvar. It contains T1-weighted contrast-enhanced MRI images categorized into four classes: glioma, meningioma, pituitary tumor, and normal. The dataset includes approximately 7,023 images with a balanced class distribution, making it suitable for multi-class classification tasks. Images are stored in JPEG format with varying resolutions and are resized to 256 × 256 during preprocessing to match CNN input requirements. Due to its diversity and clinical relevance, this dataset is widely used for benchmarking deep learning-based brain tumor classification models.

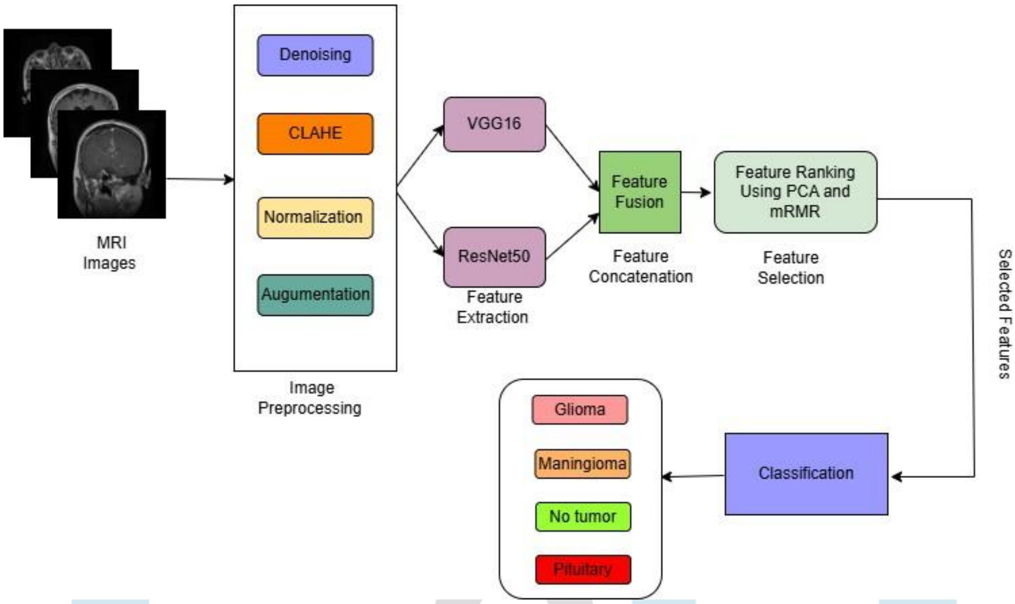

Figure 1: Proposed Methodology Following is the

main algorithm used for the proposed methodology

Algorithm 1: Proposed Hybrid Feature Fusion and Selection Framework Input:
Image dataset stored in folders

Output:
Classification accuracy, precision, recall, F1-score, confusion matrix

Step 1: Data Acquisition and Splitting

1.1 Load dataset using an image datastore with labels from folder names.
1.2 Split dataset into:

- Training set DtrainD_{train}Dtrain (70%)
- Temporary set (30%)
  1.3 Further split temporary set into:
- Testing set DtestD_{test}Dtest (15%)

Step 2: Load Pre-trained Models

2.1 Load **ResNet50** model M1M_1M1
2.2 Load **VGG16** model M2M_2M2
2.3 Select feature extraction layers:

- ResNet50 → avg_pool
- VGG16 → fc6

Step 3: Feature Extraction

For each image x∈Dtrain,Dtestx \in D_{train}, D_{test}x∈Dtrain,Dtest:

3.1 Resize image to match network input size
3.2 Convert grayscale to RGB if required
3.3 Extract deep features:

- F1=M1(x)F_1 = M_1(x)F1=M1(x) (ResNet50 features)
- F2=M2(x)F_2 = M_2(x)F2=M2(x) (VGG16 features)

3.4 Store extracted features:

- FtrainResNet,FtestResNetF_{train}^{ResNet}, F_{test}^{ResNet}FtrainResNet,FtestRes-Net

- FtrainVGG,FtestVGGF_{train}^{VGG}, F_{test}^{VGG}FtrainVGG,FtestVGG

Step 4: Feature Normalization

4.1 Apply z-score normalization on training features:

$$F' = F - \mu / \sigma$$

4.2 Apply same μ, σ to test features

Step 5: Individual Model Evaluation

5.1 Train SVM classifier using ResNet features
5.2 Train SVM classifier using VGG features
5.3 Compute accuracy and predictions for both

Step 6: Feature Fusion

6.1 Reduce VGG feature dimension to match ResNet:

$$FVGG \rightarrow FVGG(1:2048)$$

6.2 Concatenate features:

$$Ffusion = [FResNet, FVGG]$$

6.3 Train classifier using fused features

Step 7: Dimensionality Reduction (PCA)

7.1 Apply Principal Component Analysis on fused training features
7.2 Compute cumulative variance
7.3 Select number of components kkk such that:

$$\sum_{i=1}^{k} variancei \geq 98\%$$

7.4 Project both train and test features into reduced space

Step 8: Feature Selection (mRMR)

8.1 Apply Minimum Redundancy Maximum Relevance (mRMR)
8.2 Rank features based on importance
8.3 Select top K=150K = 150K=150 features

Step 9: Classification

9.1 Compute class weights to handle imbalance:

$$w_i = \frac{N}{C \cdot n_i}$$

9.2 Train multi-class SVM using ECOC with:

- RBF kernel
- Automatic kernel scale
- Class weights

9.3 Predict labels for test data

Step 10: Performance Evaluation

10.1 Compute accuracy:

$$Accuracy = \frac{Correct\,Predictions}{Total\ Samples}$$

10.2 Compute confusion matrix

10.3 Compute metrics:

- Precision
- Recall
- F1-score

Step 11: Output Results

11.1 Report:

- Accuracy (ResNet, VGG, Fusion, Fusion+FS)
- Feature dimensions
- Trainingtime

Evaluation metrics

In figure1, the proposed hybrid framework formulates image classification as a multi-stage optimization problem that integrates deep feature learning, subspace projection, and information-theoretic feature selection. Initially, two deep networks (ResNet50 and VGG16) map input images into complementary high-dimensional feature spaces, capturing both structural and semantic representations. These features are fused to form an enriched representation, which increases discriminative power but also introduces redundancy. To address this, Principal Component Analysis (PCA) projects the fused features into an optimal lower-dimensional orthogonal subspace by maximizing variance preservation. Subsequently, mRMR-based feature selection refines the representation by maximizing mutual information with class labels while minimizing inter-feature redundancy, resulting in a compact and highly informative feature set. The final classification is performed using a kernel-based SVM, which constructs a nonlinear decision boundary in a high-dimensional space. Additionally, class imbalance is handled through weighted optimization to ensure balanced learning. From a learning theory perspective, the framework effectively balances the bias–variance trade-off, where feature fusion reduces bias and feature reduction minimizes variance, leading to improved generalization.

Overall, the proposed approach theoretically achieves an optimal balance between feature richness, compactness, and discriminability, resulting in enhanced classification accuracy with reduced computational complexity.

4. Results and Discussion

4.1 Confusion Matrix Analysis

To evaluate classification performance in detail, four confusion matrices corresponding to ResNet50, VGG16, Fusion, and Fusion + Feature Selection (FS) models are analyzed. These matrices provide insight into class-wise prediction behavior, including true positives, false positives, and misclassification patterns.

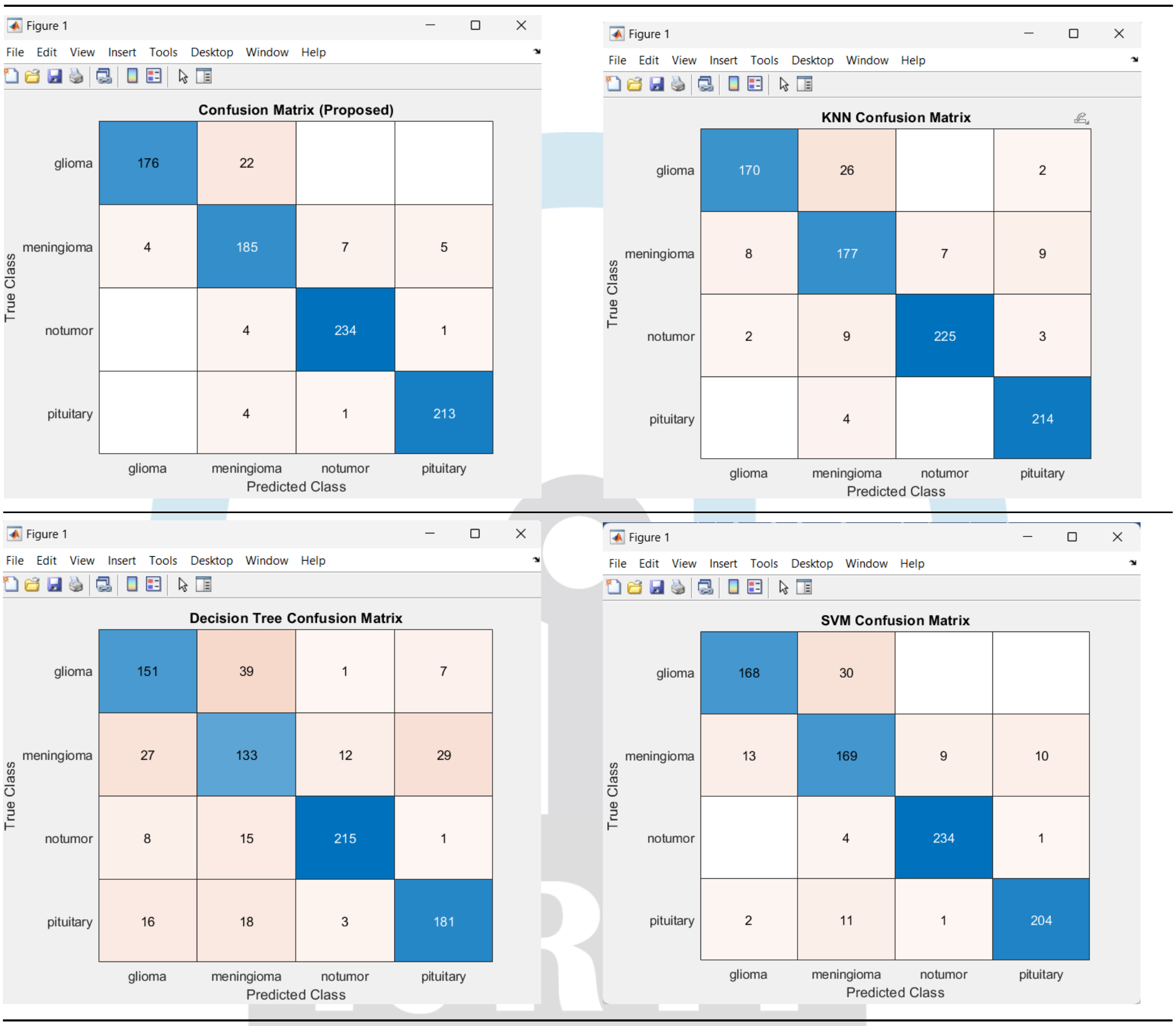

Figure 2: Confusion matrix of poposed method, Decision tree, KNN and SVM Table 2:

Comparative Confusion Matrix Analysis

Model	Key Observation	Strength	Limitation
ResNet50	Moderate misclassification between similar classes	Good feature extraction capability	Slight confusion in boundary classes
VGG16	Higher misclassification compared to ResNet50	Stable predictions	Less discriminative features
Fusion	Reduced misclassification across all classes	Complementary feature learning	Increased computational cost
Fusion + FS	Balanced classification with minimal confusion	High precision with compact features	Slight drop in accuracy vs Fusion

The table 2 shows that ResNet50 is good at extracting features with a number of misclassifications while VGG16 has more misclassifications because its features are not very distinctive even though it makes stable predictions. The Fusion model greatly reduces misclassifications by using deep features but it costs more to compute. In contrast the Fusion with Feature Selection model provides classification with little confusion and a smaller set of features with only a small decrease in accuracy making it the most efficient one overall. The ResNet50 model achieves feature extraction and moderate misclassifications. The Fusion. Fusion with Feature Selection model work well, with ResNet50 and VGG16 features.

4.2 Quantitative Performance Evaluation

Table 3: Performance Comparison of Models

Model	Accuracy (%)	Time (s)	Precision	Recall	F1 Score	Feature Size
ResNet50	93.69	2.34	0.9401	0.9342	0.9353	2048
VGG16	93.57	3.84	0.9356	0.9325	0.9333	2048
Fusion	**94.51**	3.93	**0.9465**	**0.9426**	**0.9434**	4096
Fusion + FS	94.39	**0.34**	0.9444	0.9414	0.9421	**150**

Table 3 shows that the Fusion model gets the accuracy of 94.51%. This proves that combining features really works. The Fusion model with Feature Selection keeps an accuracy of 94.39%. It reduces the number of features from 4096 to 150 which makes it more efficient. Fusion models work better than models. Feature selection is useful because it helps us keep the features. The Fusion model with Feature Selection is a choice because it gives us a balance between high performance and low computational cost. This is what makes the Fusion model with Feature Selection practical for real-world use. We have two options: the Fusion model and the Fusion model with Feature Selection. Both of these options give us accuracy. The Fusion model with Feature Selection is more efficient. The Fusion model, with Feature Selection is a choice when we think about efficiency.

4.4 Model Comparison (Accuracy vs Time)

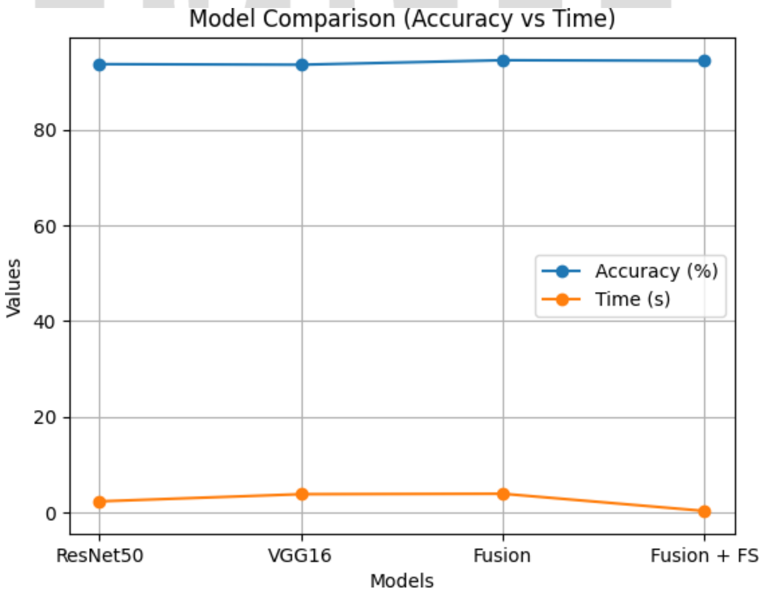

Figure 3: Model Comparison

- **ResNet50:** Fast and accurate, suitable for baseline applications.
- **VGG16:** Higher computational time with slightly lower accuracy, making it less efficient.
- **Fusion:** Highest accuracy but also highest computational cost due to feature concatena-tion.

- **Fusion + FS: Best efficiency**-performance balance, reducing time from 3.93s to 0.34s while maintaining high accuracy.

Feature selection plays a critical role in reducing computational overhead without sacrificing performance.

4.5 Comprehensive Model Comparison (Figure Analysis)

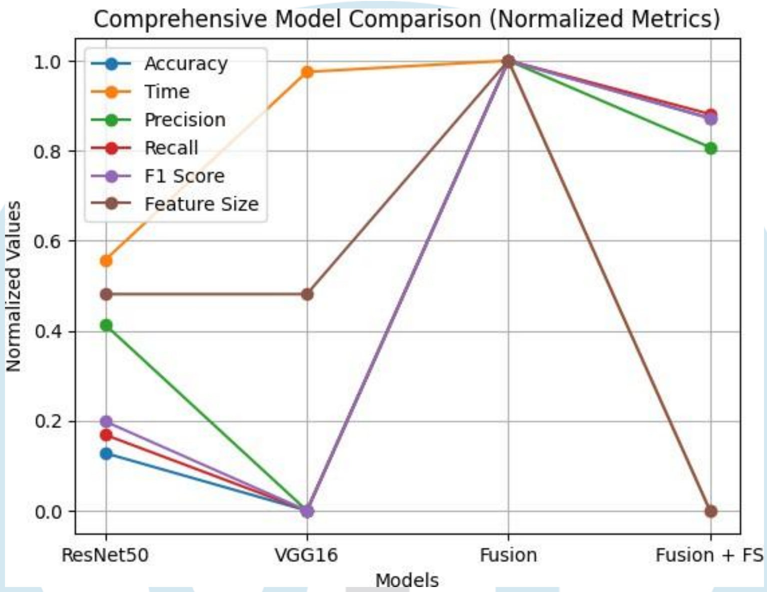

Figure 4: Comprehensive Model analysis

Figure 4 shows how all the models behave. You can see that the Fusion model gets accuracy but it takes a lot of computer time so it is good for performance. The Fusion + Feature Selection model works well. It uses computer time and it is still very accurate. The ResNet50 and VGG16 models do not work well. They are not very efficient. The Fusion model is the best for getting performance but the Fusion + Feature Selection model is a good solution, for everyday use because the Fusion + Feature Selection model balances being efficient and getting good accuracy.

5. Conclusion

This study is about finding a way to classify images. It uses two things called ResNet50. Vgg16 to do this. The study also finds a way to pick the important features for classifying images. The results are really good. The images are classified 94.51 percent of the time. This is better than using ResNet50 or just VGG16. The study also shows that we can pick the important features and still get really good results. We can go from 4096 features to 150 features and still get it right 94.39 percent of the time. So, the computer handles things pretty smoothly and doesn't get tripped up easily. But if you take a closer look at its mistakes, you'll notice this method isn't perfect—errors still pop up. Performance numbers like precision, recall, and F1 score all look solid. We compared the models and noticed there's always a trade-off. If you push for the highest accuracy, the computer burns through a lot of power. The Fusion model is great when you just want strong results. But if you're working with limited resources or need to run things in real time, the Fusion + Feature Selection model is a better bet. It manages to strike a decent balance—you get good accuracy without draining too much power, which is ideal when resources are tight. The Fusion + Feature Selection model is suitable, for applications where ResNet50 and VGG16 and computer power're limited.

References

[1] S. Bauer et al., "A survey of MRI-based medical image analysis for brain tumor studies," *Physics in Medicine & Biology*, vol. 58, no. 13, pp. R97–R129, 2013.

[2] A. Kumar et al., "Brain tumor classification using machine learning: A review," *Multimedia Tools and Applications*, vol. 79, pp. 1–25, 2020.

[3] G. Litjens et al., "A survey on deep learning in medical image analysis," *Medical Image Analysis*, vol. 42, pp. 60–88, 2017.

[4] K. He et al., "Deep residual learning for image recognition," in *Proc. CVPR*, 2016, pp. 770–778.

[5] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *ICLR*, 2015.

[6] H. Talo et al., “Automated classification of brain MRI using deep CNN with fusion,” *Applied Sciences*, vol. 9, no. 3, 2019.

[7] I. T. Jolliffe, *Principal Component Analysis*, Springer, 2002.

[8] H. Peng et al., “Feature selection based on mutual information: Criteria of max-dependency, max-relevance, and min-redundancy,” *IEEE TPAMI*, vol. 27, no. 8, pp. 1226–1238, 2005.

[9] A. Jhariya, D. Parekh, J. Lobo, S. Patil, and T. Choudhury, “Distance analysis and dimensionality reduction using PCA on brain tumour MRI scans,” *EAI Endorsed Transactions on Pervasive Health and Technology*, 2024.

[10] B. R. Rakesh Babu, V. Rajesh, B. V. Rajanna, and S. H. Hasane Ahammad, “Brain tumor classification using PCA-NGIST features with an enhanced RELM classifier,” *Bulletin of Electrical Engineering and Informatics*, 2025.

[11] F. Demir and Y. Akbulut, “A new deep technique using R-CNN model and L1NSR feature selection for brain MRI classification,” *Biomedical Signal Processing and Control*, 2022.

[12] M. J. Saadh, R. J. Al-Badr, D. Sur, A. M. A. Ali Al-Nuaimi, and B. Farhood, “Reproducible meningioma grading across multi-center MRI protocols via hybrid radiomic and deep learning features,” *Neuroradiology*, 2025.

[13] A. Biswas and M. S. Islam, “A hybrid deep CNN-SVM approach for brain tumor classifi-cation,” *Journal of Information Systems Engineering and Business Intelligence*, 2023.

[14] S. M. Ganie, R. C. Tanguturi, and M. M. Alfuraydan, “Explainable artificial intelligence-infused hybrid transfer learning framework with multiscale feature fusion for brain tumor detection and classification,” *Engineering Applications of Artificial Intelligence*, 2026.

[15] A. Bang, V. Bajpai, S. Magar, R. Bagde, and P. Jamadar, “Integrating deep and machine learning techniques for brain tumor detection,” in *Proc. 2nd Int. Conf. Advancement in Computation and Computer Technologies (InCACCT)*, 2024.