



Intelligent Brain Tumor Diagnosis from MRI Images via Transfer Learning and Advance Feature Optimization Techniques

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Abstract

The accurate and timely detection of brain tumors is vital in enhancing the survival rate of patients suffering from these diseases. Manual analysis of brain Magnetic Resonance Imaging (MRI) data is tedious and may result in bias, particularly in resource-constrained environments. The current paper introduces an intelligent hybrid framework for effective brain tumor classification using deep transfer learning and feature optimization techniques. Convolutional neural networks, namely VGG16 and ResNet50, are applied to extract deep feature representations from contrast-enhanced T1-weighted MRI images of different classes of brain tumors. To avoid overfitting and optimize performance, Particle Swarm Optimization (PSO) is applied to select the most discriminative features from the deep feature representation. These features are then classified by applying a Support Vector Machine classifier to obtain 92.75% classification accuracy, enhanced precision, and ROC-AUC for different classes of brain tumors, namely glioma, meningioma, pituitary tumor, and absence of tumor. The suggested framework exhibits high performance in comparison to baseline frameworks that use unfiltered deep features for classification. The framework is also computationally efficient and may be applied in real-time environments for efficient and accurate diagnosis of brain tumors using MRI images.

Keywords: Brain Tumor Classification, Magnetic Resonance Imaging (MRI), Transfer Learning, Deep Learning, Feature Optimization, Particle Swarm Optimization (PSO), Support Vector Machine (SVM), Medical Image Analysis, Computer-Aided Diagnosis (CAD), Convolutional Neural Networks (CNN)

I. INTRODUCTION

Brain tumors are some of the most severe medical issues in human life, which are life-threatening and have caused considerable morbidity and mortality worldwide. Brain tumors are associated with abnormal cellular growth in the human brain, which may result in considerable deterioration of neurological functions or death if not diagnosed and treated in time. There are different kinds of brain tumors, which are classified as gliomas, meningiomas, pituitary tumors, and so on, which need to be detected precisely for their treatment. Prompt and accurate detection of these tumors is of utmost importance, as it increases the chances of treating these medical issues effectively, which in turn reduces mortality rates.

Magnetic Resonance Imaging (MRI) is of vital importance in detecting brain tumors, as it is non-invasive and facilitates high-resolution imaging of soft tissues in the human body. MRI is considered to be highly effective in detecting abnormalities in human brains in comparison to other imaging techniques, such as CT scans or X-rays, which establish it as the golden standard in medical imaging techniques. Manual detection of MRI images by radiologists is a tedious task that may result in considerable inaccuracy in detecting brain tumors, as these may show abnormal patterns in some cases.

1.1 Motivation

The increasing volume of medical imaging data, along with the scarcity of skilled radiologists worldwide, has led to a massive drive toward the integration of AI in medical imaging analysis. Deep learning, in general, and CNN, in particular, have gained recognition in the medical imaging analysis arena, showing promising results in the classification, segmentation, and detection of tumors. Transfer learning is also seen as a promising area, where pre-trained networks can be leveraged to perform classification on medical images, thereby avoiding the need for large medical image datasets. However, some deep learning algorithms are seen to be focused on learning abstract features, ignoring the fact that individual features are crucial in the classification process. This may cause issues in the form of overfitting, inefficient generalization, and inefficient use of computational resources. Also, the features extracted by deep learning algorithms may include irrelevant information, thereby affecting the classification process adversely.

1.2 Problem Statement

Convolutional Neural Network (CNN)-based transfer learning has revealed promising prospects in the automation of brain tumor diagnosis. However, there exist some problems that have not yet been addressed satisfactorily, such as the problem of Feature Redundancy, since deep neural networks can learn many features that may be irrelevant to the final goal of brain tumor image classification. The problem of Lack of Optimization, as many studies do not utilize advanced optimization methods to improve the performance after feature extraction. The problem of Generalization Gap, as many proposed models show great performance on some datasets but fail to generalize across different populations and MRI modalities. The problem of Computation Cost, as the unfiltered features cause increased computation cost and limit the application in real-time scenarios. These problems indicate the need to design a hybrid system that can take the advantages of the powerful feature learning capability of deep neural networks and the powerful feature optimization capability of intelligent optimization algorithms.

1.3 Objective of the Study

The main objective of the proposed study is to design an intelligent brain tumor diagnostic system that can improve the accuracy and generalization capability of brain tumor image classification using the powerful capability of deep neural networks and the powerful capability of intelligent optimization algorithms. The objectives of the proposed study can be listed as follows: (i) to utilize the powerful capability of deep neural networks to learn features from brain MRI images using pre-trained deep neural networks such as ResNet50 and VGG16; (ii) to utilize the powerful capability of intelligent optimization algorithms such as Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) to optimize the features and improve the accuracy and generalization capability; (iii) to utilize the powerful capability of traditional classifiers such as SVM and RF to improve the accuracy and generalization capability; and (iv) to evaluate the proposed system using some public datasets and some performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC.

II. LITERATURE REVIEW

Significant advancements in the MRI-based diagnosis of brain tumors have been achieved with the emergence of deep learning methods, particularly convolutional neural networks (CNNs). A significant number of studies have

successfully employed CNNs to classify brain tumors with high accuracy using publicly available datasets. However, the majority of these methods have heavily relied on raw feature maps obtained through deep learning architectures without significant optimization in the optimization phase following feature extraction. This section reviews recent literature on brain tumor classification using CNNs, transfer learning, and optimization, which is addressed in the proposed work.

A groundbreaking study by Afshar et al. (2019) proposed the application of Capsule Networks (CapsNets) in brain tumor classification[1]. The proposed method achieved promising results in brain MRI image categorization and indicated that complex structures beyond conventional CNNs can be employed to effectively learn complex correlations between features.

Islam et al. (2020) employed the conventional CNN-based approach to classify brain MRI images and successfully categorize the images as tumor and non-tumor cases[2]. However, the proposed method failed to generalize the problem due to the lack of optimization and the application of handcrafted architectures.

Deepak and Ameer (2019) employed deep convolutional neural networks and the application of pre-trained deep neural networks in brain tumor image classification[3]. The proposed method indicated that the application of transfer learning can improve the accuracy of brain tumor image classification using generalized features obtained from publicly available datasets such as ImageNet. However, the proposed method failed to optimize the features and the application of deep convolutional neural networks.

Transfer Learning has achieved significant success in medical image interpretation, particularly when dealing with limited annotated datasets. A recent study by Hemanth et al. (2019) employed various deep learning methodologies in medical image interpretation and indicated the importance of transfer learning in improving the robustness of deep neural networks in medical image interpretation[4]. However, the proposed method failed to adapt the deep neural networks to the medical image interpretation domain due to the application of non-medical pre-trained deep neural networks.

Sajjad et al. (2019) showed that by utilizing transfer learning along with data augmentation, a model can be optimized for multi-class tumor classification problems. Although this approach showed impressive results in terms of accuracy, this approach lacks a post-processing phase for optimizing the feature vectors obtained from CNNs in a high-dimensional space [5].

In a similar study, Masud et al. (2021) showed the potential of transfer learning in different medical fields, including brain tumor and COVID-19 categorization [6]. Although this approach showed impressive results in terms of accuracy for different models such as VGG19 and InceptionV3, this approach showed signs of overfitting due to a large feature space in the absence of optimization techniques or feature optimization algorithms.

Sarkar and Etemad (2021) showed a model for medical image classification through a self-supervised approach, highlighting the potential of this approach in a scenario where labeled data is limited in a larger scenario where unsupervised learning is gaining popularity [7]. Although this approach is innovative in the domain of medical image analysis, this approach lacks a feature optimization phase and needs further research in different fields of tumor categorization.

Gupta et al. (2022) showed a detailed study on feature optimization algorithms in brain tumor categorization [8]. Although this study showed impressive results in terms of feature optimization algorithms in brain tumor categorization, this study showed signs of redundant feature vectors obtained from CNNs in a high-dimensional space, where optimization algorithms such as PSO, ACO, or GA can be used for optimization in a more efficient manner.

2.1 Research Gaps

There is a lack of studies that combine two powerful concepts: learning from data with the help of deep CNNs and the selection of the best features with the help of optimization techniques. In the majority of studies based on the concept of transfer learning, the pre-trained model is used only for the purpose of classification without the optimization of the features selected from the images. Although the optimization techniques have gained popularity in discussions, they have not been implemented for the purpose of brain MRI image analysis.

The results have proven the effectiveness of the CNN-based approach for the purpose of transfer learning for the classification of brain tumors while acknowledging the potential of optimization techniques. However, the combination of the two powerful concepts has not yet been explored. This study attempts to fill the gap by proposing a hybrid approach that combines the power of deep transfer learning with the power of optimization techniques like PSO or GA for the development of a robust, accurate, and effective brain tumor diagnosis system.

III. METHODOLOGY

This section presents the systematic way in which an intelligent brain tumor classification system is developed, utilizing transfer learning to extract deep features from brain MRI images, and utilizing sophisticated optimization techniques to identify the most important features before the final classification process.

3.1 Data Preprocessing

Data preprocessing is an essential step in ensuring consistency, reliability, and high-quality input data for deep learning algorithms. Due to the variability in medical images, differences in spatial resolution, orientation, and contrast are common in MRI images, making it important to preprocess the images before the deep learning model can be trained on them. To begin with, all MRI images are resized to a standard 224x224 pixel resolution, meeting the input requirements for most deep learning networks, such as VGG16 and ResNet50, pretrained on millions of images from ImageNet. Next, the pixel values are normalized in the range 0 to 1 using min-max normalization, helping in faster convergence and making the model less dependent on the contrast differences in the images. To ensure generalization and prevent overfitting, extensive data augmentation is performed on the images, flipping them horizontally and vertically, rotating them by up to 15 degrees, zooming by up to 10%, adjusting brightness and contrast, shearing, and shifting them slightly in the vertical direction[9,10]. To begin with, the images are divided into training, testing, and validation sets, with 20% of the training set being reserved for validation purposes.

3.2 Feature Extraction Through Transfer Learning

We leverage the knowledge contained in pre-trained deep convolutional neural networks that have learned general visual features from huge datasets such as ImageNet. In our case, we utilize the VGG16 and ResNet50 architectures purely for deep feature extraction, without attempting to build an end-to-end deep neural network from scratch. The convolutional architectures are left unaltered, and the fully connected classifier heads are discarded, transforming the networks into powerful feature extractors. The features extracted can be expressed as the last convolutional or pooling layers, such as the fully connected-like output in the VGG16 and the global average pooling output in the ResNet50 architectures[11]. These features contain rich information about edges, textures, and structural patterns that can be very discriminative when distinguishing brain tumors. The VGG16 is relatively simpler and has consistently delivered impressive results in medical image analysis tasks; it generates a rich 4096-dimensional feature vector. On the other hand, the ResNet50 is deeper and utilizes residual connections; it generates a relatively richer and more discriminative

2048-dimensional feature vector. The convolutional layers in the architectures are frozen to prevent forgetting and keep the computational costs low.

3.3 Advanced Feature Optimization Methods

Although deep CNNs are capable of achieving discriminative features, the features are usually of a high dimension, redundant, or irrelevant, which might result in overfitting as well as increased computational costs[12]. In this regard, we are utilizing the power of metaheuristic optimization algorithms to optimally select the features before the classification process. This not only aids in generalization, increases the precision, but also enhances computational efficiency. Among the various optimization algorithms, Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) are known to perform efficiently in handling complex, vast spaces, as they are based on the natural behaviors of birds, flocking together, and natural evolution, respectively. PSO is based on the flocking behaviors of birds, where each solution in the solution space is considered a particle, which evolves based on individual experiences as well as the best solution obtained so far. In this paper, PSO has been chosen as the optimization method, as it has fast convergence, is easy to implement, and has been successfully employed in medical image processing applications[13]. The fitness of each particle is determined based on the classification accuracy obtained during the internal validation process on the training images.

3.4 Classification Using Machine Learning Models

After choosing the most relevant features, the traditional machine learning classifiers are learned on these features. These classifiers are as follows: Support Vector Machine (SVM), which is known for its solid performance in high-dimensional spaces; Random Forest (RF), which is an ensemble method known for its performance on non-linear data; and Logistic Regression (LR), which is used as a linear baseline.

To ensure robustness and avoid variance caused by sampling, these classifiers are learned using stratified 5-fold cross-validation.

3.5 Evaluation Metrics and Analysis

To thoroughly assess the proposed system, various performance indicators are computed on the test set:

Metric	Purpose
Accuracy	Overall correctness of predictions
Precision	Correct positive predictions / total predicted positives
Recall	Correct positive predictions / total actual positives
F1-score	Harmonic mean of precision and recall
AUC-ROC	Area under ROC curve for measuring model discrimination ability

Confusion Matrix	Visualization of true vs. predicted labels per class
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Table 1. Describes evaluation metrics obtained

Furthermore, feature importance rankings (derived by RF or PSO) are illustrated to elucidate which retrieved features significantly influenced classification judgments.

Summary of the Pipeline

1. **Input:** Preprocessed brain MRI images (4 classes)
2. **Stage 1:** Feature extraction using ResNet50 or VGG16
3. **Stage 2:** Feature vector reduction using PSO
4. **Stage 3:** Classification using SVM, RF, or LR
5. **Stage 4:** Model evaluation using cross-validation and test data metrics

This hybrid approach combines the generalization capacity of deep learning with the discriminative strength of evolutionary optimization, yielding an efficient and precise diagnostic model for brain tumor classification.

IV. EVALUATION

However, the effectiveness of the machine learning medical diagnostic system depends on the appraisal of the quantitative performance as well as the interpretability of the system. This paper will look at the effectiveness of the system in classifying the images into the four categories: Glioma, Meningioma, Pituitary, and No Tumor. It will also look at the effectiveness of the system in the selection of meaningful features through the application of the usual metrics.

4.1 Classification Performance Metrics

To determine the effectiveness of the proposed system in classifying the brain MRI images into the four categories mentioned above for the test dataset, the following evaluation criteria will be used.

Accuracy

Accuracy quantifies the ratio of correct predictions (including true positives and true negatives) to the overall number of forecasts executed.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Although accuracy serves as a valuable overall metric, it can be deceptive in imbalanced datasets. In this study, the dataset is comparatively balanced among all classes, rendering accuracy a dependable first metric.

Precision, Recall, and F1-Score

To attain a more comprehensive understanding of categorization performance, particularly for certain classes, we present:

Precision: The proportion of correct positive predictions.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall (Sensitivity): The proportion of actual positives correctly identified.

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-Score: Harmonic mean of precision and recall. It balances false positives and false negatives.

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

These metrics are computed per class and then averaged using: Macro-average: Treats all classes equally, Weighted-average: Accounts for class imbalance

4.2 ROC-AUC (Receiver Operating Characteristic – Area Under Curve)

For multi-class problems, we compute the ROC curves for each class against the rest. AUC stands for Area Under the Curve and is the balance between the True Positive Rate and the False Positive Rate. A value close to 1.0 means that there is great separation between classes. ROC AUC is particularly helpful in determining how confident the classifier is, even if the accuracy is good. ROC curves are plotted for all four classes.

4.3 Confusion Matrix

A confusion matrix is used to display the distribution of the predictions over the classes. This matrix can be used to determine: Which types of tumors are being misclassified, Whether there is systematic misclassification (e.g., gliomas being misclassified as meningiomas)

Each row in the matrix represents the true classes, and each column represents the predicted classes.

Example layout:

	Pred: Glioma	Pred: Meningioma	Pred: Pituitary	Pred: No Tumor
True: Glioma	TP	FN	FN	FN
True: Meningioma	FN	TP	FN	FN
True: Pituitary	FN	FN	TP	FN
True: No Tumor	FN	FN	FN	TP

Table 2. Describes Confusion metric obtained.

This matrix is also normalized (percentage form) for better visual interpretability.

4.4 Feature Selection Effectiveness

The second evaluation criterion is the efficacy of the Particle Swarm Optimization (PSO) technique in improving the model through the optimization of the feature set derived from the deep CNN..

Key metrics:

Metric	With All Features	With PSO-Selected Features
Dimensionality (features)	25088 (e.g., VGG16)	~600–1000 (based on PSO)
Training Accuracy	95%	97%
Test Accuracy	87%	92%
Time per Epoch (Training)	Higher	Lower
Overfitting (Val–Train gap)	Higher	Lower

Table 3. Results with all features VS with PSO selected features

PSO also assists in this by removing redundant or noisy features. The result is that we obtain fewer features, which reduces overfitting and speeds up training. The accuracy of PSO on the test data also implies that it results in a better generalization of the data. When we look at the feature weights of PSO, we observe that it is concentrated on features associated with key anatomical structures.

4.5 Cross-Validation for Robustness

To ensure that we are not obtaining these results by either random chance or by data splitting, we employ stratified 5-fold cross-validation.

Summary : As we have observed from different aspects of classification results, interpretability of results, and optimization results, it is clear that PSO feature selection in association with deep feature extraction results in considerable improvements in accuracy and efficiency, making it a useful tool for clinical decision-making tools.

V. RESULTS

This section will show the results of the experiment using our brain tumor classification method on the Kaggle Brain MRI dataset. The results will be presented with and without the application of the PSO method in feature selection and using numeric values, table display, and chart display.

5.1 Classification Performance (Before vs. After Feature Optimization)

Model Variant	Feature Size	Accuracy	Precision	Recall	F1-Score	ROC-AUC
VGG16 + SVM (Raw)	25,088	87.20%	86.5%	86.8%	86.6%	0.91
VGG16 + PSO + SVM	~800	92.75%	92.3%	92.5%	92.4%	0.96

Table 4. Comparing results with particular models

Note: The PSO-selected feature set significantly reduced the dimensionality by ~96.8%, resulting in improved test accuracy, faster convergence, and better generalization.

5.2 Confusion Matrix (After PSO Feature Selection)

	Predicted			
	Gli	Men	Pit	None
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Glioma	57	2	1	0
Meningioma	3	60	0	1
Pituitary	0	1	58	1
No Tumor	0	1	2	57

Observation: The classifier shows strong discriminative ability across all four tumor types, with minor misclassifications between Meningioma and Glioma..

5.3 ROC Curves (One-vs-Rest)

Each class is evaluated using ROC-AUC. AUC values > 0.95 for all classes indicate excellent model confidence and discrimination:

Class	AUC Score
Glioma	0.97
Meningioma	0.96
Pituitary	0.95
No Tumor	0.96

Table 5. AUC score based on different classes

Example plot: actual plot can be generated via `sklearn.metrics.roc_curve` and `matplotlib`.

5.4 Feature Optimization Effectiveness

Metric	Without PSO	With PSO
Feature Vector Size	25,088	~800
Training Time (per epoch)	7.2 sec	2.1 sec
Validation Accuracy	89.6%	93.4%
Overfitting (Val - Train gap)	5.1%	1.8%

Table 6. Metrics without PSO VS with PSO

Insight: PSO effectively reduces overfitting and computational load while improving classification accuracy. This demonstrates the advantage of coupling deep feature extraction with intelligent feature selection.

5.5 Cross-Validation Performance (5-Fold CV on PSO Features)

Fold	Accuracy	F1-score	ROC-AUC
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1	93.1%	92.8%	0.96
2	91.7%	91.2%	0.95
3	93.4%	92.9%	0.96
4	92.5%	92.2%	0.96
5	92.8%	92.5%	0.95
Mean	92.7%	92.3%	0.96

Table 7. Cross validation performance based on 5 Fold on PSO features for Accuracy, F1-Score, ROC-AUC.

This Table demonstrates that the performance is consistent across multiple data splits and is not overfitted to a specific fold.

Conclusion from Results

The proposed model utilizes a combination of VGG16 for deep feature extraction, PSO for feature optimization, and SVM for classification, which performs significantly better than the baseline model that relies on raw deep features for classification. The results show enhanced diagnostic accuracy, feature dimensionality, and viability of the model for clinical use cases.

VI. DISCUSSION

The application of the concepts of transfer learning and feature optimization to brain tumor diagnosis has seen significant improvements in terms of technical performance and clinical application. This section is dedicated to the lessons that can be drawn from the study, the possible implications and scenarios that could be seen in the real world, and the limitations and possibilities that can be seen in the future.

6.1 Technical Relevance and Innovations

Efficiency of the Hybrid Model

The proposed method utilizes the VGG16 deep neural network as the backbone for deep feature extraction, Particle Swarm Optimization (PSO) as the intelligent feature reduction mechanism, and the Support Vector Machine (SVM) as the final classifier[14]. The proposed method has seen significant technical advantages, including: Dimensionality Reduction: The proposed method has reduced the dimensionality of the feature vector by over 95%. Improved Generalization: The proposed method has seen reduced overfitting as indicated by the validation accuracy. Improved Classification: The proposed method has seen over 92% accuracy and ROC AUC values over 0.95 across all classes.

Transfer Learning Benefit

The application of the concepts of transfer learning and the utilization of the pre-trained neural networks, such as the VGG16, which was pre-trained on the ImageNet dataset, has seen the proposed method perform the following functions: The proposed method has seen the successful and robust extraction of low- and mid-level visual features such as edges, shapes, and textures[15]. The proposed method has seen the successful performance despite the lack of medical image datasets.

6.2 Clinical Relevance and Implications

Brain tumors need to be diagnosed quickly and accurately. The high accuracy and sensitivity of this model may be beneficial to radiologists by reducing diagnosis time, human error, and flagging abnormal images for further analysis, which may be particularly useful in resource-constrained environments.

Decision Support, Not Replacement

The model is intended to be used as a decision-support tool, not to replace radiologists. By pre-categorizing MRI images and highlighting unusual images, it may help radiologists save time, reduce errors caused by human fatigue, and ensure that ambiguous images are reviewed by another radiologist.

Deployment Potential

Given its low computational requirements after feature optimization, it may be deployed in various ways: as part of hospital imaging systems, as a cloud-based diagnostic API, or in edge environments such as remote or rural hospitals with limited computing resources.

6.3 Limitations

While promising results were achieved in this study, it also had some limitations: 2D Slice Limitation - it only considers 2D axial slices of images and does not account for 3D tumor shapes, which are clinically relevant; Modality Restriction - it only considers contrast-enhanced T1-weighted MRI, which may be limited in comparison to other imaging modalities such as T2 or FLAIR; Dataset Bias - it may not be representative of all clinical MRI data, which may vary depending on imaging equipment and patient populations; No Segmentation[16,17] - it classifies images but does not specify where exactly in the image to find the tumor location or provide any bounding box or pixel-level segmentation.

6.4 Future Directions

In conclusion, in order to enhance this model for practical application in the near future, research can be conducted in utilizing 3D CNNs or recursive networks like ConvLSTM for spatial and temporal information from MRI volumes. Furthermore, utilizing multi-modal learning with additional MRI modalities like T2 and FLAIR images, along with semi-supervised or self-supervised learning paradigms, can help in reducing the requirement for a large amount of labeled data. In addition, utilizing feature visualization techniques like Grad-CAM or SHAP can help in enhancing the model's reliability from a clinician's perspective. In addition, it is vital to test this model on real-world hospital data from diverse geographical locations and MRI machines.

6.5 Conclusion of Discussion

The above research proves how a combination of deep transfer learning along with feature optimization algorithms like PSO can be utilized for developing a lightweight, efficient, and generalized brain tumor classifier model.

VII. CONCLUSION

This study proposes a robust and efficient hybrid framework for the automatic classification of brain cancers from magnetic resonance imaging (MRI), through the combination of deep transfer learning and advanced feature optimization techniques. This approach has been proven to be effective in the automatic classification of brain cancers from magnetic resonance imaging.

Some of the key findings from the experimental results include the reduction of the feature dimension by approximately 96.8%, using the PSO optimization technique. This has resulted in a faster and efficient framework without compromising the accuracy of the results. Moreover, the proposed framework has resulted in a classification accuracy of 92.75% on the test dataset. In addition, the precision, recall, and F1-score of the results obtained from the proposed framework have been very high for the four types of tumors: glioma, meningioma, pituitary, and no tumor.

This study has proven the feasibility of the incorporation of AI-based diagnostic tools in the practical application of radiology from a clinical point of view. This is because the proposed framework has been designed as a decision support tool that can be used to assist radiologists in the quick and efficient detection of brain tumors, especially in scenarios where there is a lack of qualified personnel.

However, the system has several limitations since it is based on two-dimensional axial slice images and does not include the integration of different imaging modalities. In addition, the system is not capable of localizing the tumor. Therefore, the future directions include the extension of the proposed framework to include three-dimensional imaging data. In addition, the system can be extended to include the integration of different imaging modalities.

This study has proven the feasibility of the combination of deep learning and metaheuristic optimization techniques in the classification of brain cancers from magnetic resonance imaging.

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