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Advanced Residual Network Architecture for Automated Brain Tumor Diagnosis: The MesResNet50 Approach

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Abstract: Identifying tumors in the brain is very crucial for early diagnosis that supports in developing successful therapeutic treatments. Traditional methods were based on manual feature extraction, and classic machine learning techniques lack the ability to explain the intricate variations found in the morphology and positioning of brain tumors. In this paper, we propose MesResNet50, a modified residual network architecture for classifying different brain tumor types from magnetic resonance imaging (MRI) images. MesResNet50 utilizes transfer learning like partial layer freezing and possesses a strong classification head in an effort to improve generalization and performance. The dataset consists of 7023 MRI scans. These scans depicted four types of tumors: no tumor, glioma, meningioma, and pituitary tumor. MesResNet50 performed better than other models like CNN, AlexNet, VGG16, and ResNet50 on major evaluation metrics. With a test accuracy of 96.80%, an F1-score of 96.69%, and a ROC-AUC of 0.9949, MesResNet50 clearly demonstrates the capabilities to discriminate between classes and has a well-balanced performance on sensitivity and specificity metrics. Such effectiveness is due to residual architecture enabling greater depth and, hence, improved feature extraction and generalization. The improved residual architecture has much greater computational cost, which can be a burden in low-resource environments. The findings demonstrate the potential of utilizing MesResNet50 as a reliable and good approach for automated diagnosis of brain tumors for clinical decision support. Future work will focus on improving efficiency for rapid inference, evaluating simpler architectures to reduce resource usage, and testing the model on multicenter datasets to enhance clinical utility.

Keywords: brain tumor detection, deep learning, ResNet50, AlexNet, medical imaging

1. Introduction

Early detection of brain tumors has a major impact on treatment results and patient survival rate. At present, radiologists manually analyze magnetic resonance imaging (MRI) to diagnose a tumor [1]. Insightful scans take a fair bit of time, and a specialist's skill is paramount to making an accurate assumption. Smaller features of the tumor may very well be omitted, and the disparity in interpretation by different individuals is the fog of war in the sample diagnosis [2].

In recent years, deep learning has become a part of addressing the issues and limitations of manual diagnosis. Many researchers have tried using Convolutional Neural Networks (CNNs) and the subsequent architectures with attributed improvements over traditional feature-engineering approaches in brain tumor classification and segmentation [3, 4]. These models learn distinctive and intricate patterns from MRIs and aid in improved classification and identification of the tumors [5, 6]. Transfer learning with attention mechanisms has also made feats in augmenting models' performances, improving their reliability in clinical settings [7]. The combined deep learning approaches, recreationally used in brain tumor diagnostics, help in transcending traditional constraints in diagnostics. It unshackles the previously held non-scalable, non-reproducible, and non-efficient restraints, augmenting and supplying the necessary aids for faster and more precise assessments of radiologists [8, 9].

The forthcoming diagram in Figure 1 illustrates the distinctions between traditional methods and neural network approaches for recognizing brain tumor detection, setting the stage for the introduction of MesResNet50.

Based on the reviewed literature, we hypothesize to investigate the performance of the MesResNet50 model in brain tumor classification based on MRI images. Moreover, we are going to assess its performance with ResNet50, CNN, VGG16, and AlexNet models. The study is driven by the need to establish the best deep learning technique to be applied in the detection of brain tumors, which may, in the process, lead to better diagnosis and management of patients.

This study adds to the growing body of literature by conducting a review of the literature related to healthcare imaging and AI

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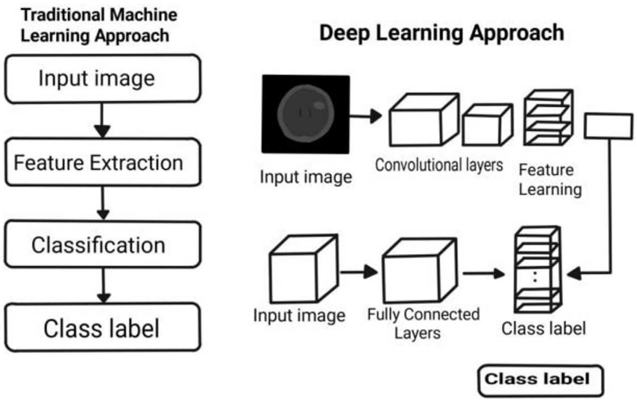
Figure 1
Traditional vs. deep learning approach



to provide guidance that may help researchers and clinicians with future research and practice [10].

This work is relevant because it addresses the gap in model-specific performance analysis in brain tumor classification while introducing a lightweight, optimized alternative to traditional architectures.

Our studies add to the growing body of literature focusing on the use of deep learning for neuroimaging by establishing a benchmark for future model development and deployment in clinical practice.

The aim of this research was:

1) To create a new brain tumor model from ResNet50.
2) To compare how well MesResNet50 performs with AlexNet, VGG16, and a standard CNN on the same dataset using uniform training parameters.
3) To assess and visualize model effectiveness through different evaluation methods including accuracy, precision, recall, F1-score, confusion matrix, and ROC curves.

To conclude, in this work, we provide an in-depth analysis of the newly adapted ResNet50 architecture to detect brain tumors and compare the results of this model to other well-known deep learning models. The methodology used in this study is described in the next sections, followed by the results obtained in the comparative analysis, and their impact on neuro-oncology and medical imaging is discussed.

2. Literature Review

Deep learning for brain tumor classification and detection has been a significant area of research over the last several years, with convolutional neural networks (CNNs) being at the forefront. This literature review compiles results of recent studies on multiple deep learning architectures that include modified versions of the ResNet50 Model to evaluate their performance relative to traditional CNNs and other architectural frameworks.

The study by Ali et al. [10] demonstrated the ability of classical CNN and ResNet50 as an effective tool in identifying and classifying brain tumors. In addition to demonstrating the differences in performance using ResNet50 on medical MR images, they discussed the training of these models and the benefits of utilizing deeper features to better distinguish between different tumor types. Their study has shown that ResNet50 remains a viable option for classification; however, their study utilized only the standard ResNet50 architecture and did not provide any novel design options or suggestions as to how well the model can explain its results and the efficiency of the number of parameters.

Asiri et al. [3] used a combination of ResNet50 and U-Net to find and classify tumors in public MRI datasets (TCGA-LGG and TCIA). Using a combination of classification and segmentation methods to detect tumors is better than either alone as shown by this method. Feature extraction and segmentation together provided a much better tumor detection capability than either alone. Their tests were limited by difficulty in achieving comparable performance across their test datasets. The ResNet50+U-Net architecture performed well, but it was very large. Unfortunately, the researchers did not consider or discuss smaller variants of this architecture, which could be used for tumor detection while keeping the number of parameters at an acceptable level.

The multiscale CNN uses a combination of feature extraction at varying resolution levels to aid in both classification and segmentation of brain lesions. This combination provides improved detection capabilities through the use of cues at varying resolutions. The authors demonstrated the value of using both local and global characteristics of brain tumors. The authors demonstrate that combining multiple scales can provide improved location and classification of brain tumors. The proposed network is relatively complex and does not have as a goal using fewer parameters or lighter-weight fusion methods. Also, this research does not clearly detail the individual contribution of the multiscale module [2].

The EfficientNet B4 model was able to automatically identify brain tumors. The authors indicated that this model is better at balancing the performance of the model with its size in comparison to larger models. They were able to demonstrate that more recent, efficient architectures can have comparable or superior performance to older deep CNN architectures when applied correctly. In order to evaluate the potential for more efficient designs, they selected the models based on their design's efficiency as well as the model's ability to perform accurately. The authors' findings are limited by the fact that they only evaluated one of these efficient models, and they did not provide examples of how a smaller module could potentially be integrated into networks to improve efficiency and clarify the architecture of those networks [11].

Jun and Zheng [12] created a deep learning model to classify brain tumors. This model uses attention mechanisms to focus on areas related to the disease. They found that attention modules help in better classification by highlighting key features. Their study suggested adding channel/spatial recalibration to the classification models. However, there are some issues: attention is added on top and often increases the number of parameters required. This study does not consider the use of lightweight attention within residual blocks or show the balance between attention strength and model size.

Tummala et al. [13] suggested using a group of Vision Transformers to classify brain tumors. They showed that these models work well using attention and patch-based methods. Their findings indicate that transformer models could be a good alternative to CNNs for processing medical images. This study points to a shift towards non-convolutional models for classification. However, transformer groups can be complex and difficult to understand in MR images. This study does not focus on small hybrid models that retain the benefits of convolutional methods while being more efficient.

3. Methodology

3.1. Dataset description

The advent of AI and deep learning, especially CNNs, has transformed the analysis of medical images by providing automated and efficient solutions for brain tumor detection, classification, and segmentation. In this section, we discuss a comprehensive description of the Brain Tumor MRI dataset from Kaggle, which is primarily associated with Masoud Nickparvar, a widely referenced resource in deep learning research for brain tumor analysis. The dataset is a publicly available collection of MRI scans intended for brain tumor detection and classification tasks.

Table 1 consolidates the principal properties of the dataset, as imputed from numerous studies published in research studies. The inconsistencies in total image numbers and resolutions underscore that researchers tend to process, subset, or enrich the base dataset for their particular model needs or to mitigate inherent data constraints. Table 1 provides a useful benchmark to appreciate the typical attributes of a dataset and the typical differences that arise in its use in the literature.

3.2. Common preprocessing strategies

Various preprocessing and data augmentation techniques to Brain Tumor MRI datasets are crucial for enhancing image quality, ensuring data consistency, reducing noise, and artificially expanding the training data volume, all of which contribute to improved model accuracy, performance, and generalization [14]. The common preprocessing steps include:

1) Normalization: Intensity normalization is frequently applied to rescale pixel values to a consistent numeric range, such as (min-max normalization) or centered around zero mean with unit variance (z-score normalization) [2].
2) Resizing: Images are scaled to even dimensions (e.g., 80 × 80, 150 × 150, 224 × 224, 227 × 227, 384 × 384, 512 × 512 pixels) to meet the input requirements to reduce the computational burden [1].
3) Noise reduction and enhancement: Methods like Gaussian filtering, contrast enhancement, and Laplacian filters are utilized to improve image clarity and sharpen features, thereby making tumor boundaries more visible [8].
4) Data augmentation: To overcome data limitations and improve model robustness against overfitting, various methods for data augmentation have been widely.
5) Geometric transformations: Random rotation (e.g., up to 25 degrees, or [−20, 20] range), horizontal/vertical shifting (e.g., up to 20%), zooming (e.g., 85% to 115%), shearing, and horizontal/vertical flipping.
6) Elastic transformation.
7) Color adjustments (e.g., contrast adjustment).

3.3. Proposed MesResNet50 architecture

ResNet-50 has become a widely used deep convolutional architecture because of its residual skip connections, which prevent vanishing gradient problems and preserve feature information for stronger representation learning. In medical imaging, particularly in MRI, ResNet-50 has demonstrated reliable performance in extracting fine-grained patterns [15, 16] demonstrated its superior performance over classic CNNs in brain tumor classification, making it a strong baseline for disease detection, segmentation, and computer-vision applications.

This section describes a novel deep learning architecture, MesResNet50, for the classification of brain tumors. The model is built upon the ResNet50 architecture [17], introducing a fine-tuning strategy and a custom classifier head.

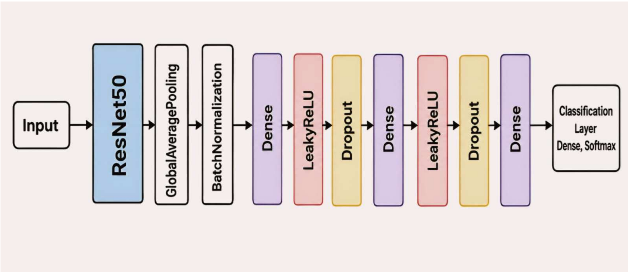
3.3.1. *Architectural design*

The MesResNet50 architecture, as shown in Figure 2, is built on ResNet50 by altering the layers in the following three ways. First, it keeps the early layers unchanged (shown in gray in the diagram) but lets the deeper layers change for better results. Next, it uses a global average pooling layer to make the data smaller before adding a new part. This new part has two dense layers with LeakyReLU and ReLU activations. The Rectified Linear Unit (ReLU) is a widely used activation function in deep learning, particularly in CNNs. It outputs the input value when positive and zero when negative, thereby enabling the neural networks to learn complex patterns. The computational simplicity of ReLU allows for faster model training compared to sigmoid or tanh functions. It also prevents vanishing gradients during backpropagation, making it effective for deep architectures, such as ResNet and computer-vision applications.

Table 1
Characteristics of dataset

Characteristic	Inferred details
Author	Masoud Nickparvar
Primary platform	Kaggle
Total images	Ranges from 1311 to ~7023
Primary categories	No tumor/healthy brain, glioma, meningioma, pituitary
Typical data splits	80% training, 20% validation/testing
Image modalities	Predominantly T1-weighted (T1w) and T1-weighted contrast-enhanced (T1-CE) MRI, with mentions of T2-weighted and FLAIR in broader contexts.
Image views	Sagittal, axial, coronal views
Image resolution	Ranges from 80 × 80 pixels up to 512 × 512 pixels, with common resized resolutions including 150 × 150, 160 × 160, 224 × 224, 227 × 227, 384 × 384

Figure 2
Proposed MesResnet50 architecture



It also uses dropout and batch normalization to improve the model and prevent overfitting. Finally, the model's output is made by a softmax layer, which helps in classifying different classes.

Customization involves two primary changes: a novel fine-tuning approach and a unique classifier.

Layer freezing and fine-tuning: The first 20 layers stay the same to keep the ImageNet-trained filters. The deeper layers are changed to learn features specific to MRI. This helps the network learn to detect brain tumor patterns in MRI scans, which are different from the features learned from ImageNet images [18, 19].

Classifier header: The classifier head, as shown in Table 2, was redesigned by adjusting the ResNet50 backbone; a new classifier head was created using a Functional Application Programming Interface (API) for more flexibility. This head is a complex, multi-layered structure, made to be stronger and to work better than a simple model. The table below shows the classifier header design.

3.4. Fine-tuning strategy

Fine-tuning Strategy: The MesResNet50 model used a special fine-tuning method. In the usual ResNet50 model, all but the last 20 layers are frozen [11]. However, in the create_mesresnet50_v2() function, only the first 20 layers were frozen. This is a smart way to use transfer learning. Freezing layers is a common method for adjusting pre-trained models. Usually, the first layers of pre-trained CNNs are frozen because they detect basic features, such as edges and colors, which work for many images [13, 18]. Deeper layers find more detailed features, helping to recognize specific parts and textures of objects [19].

The LeakyReLU activation function was used instead of the regular ReLU in the first dense layer to prevent inactive neurons and improve gradient flow. Choosing an activation function is key to adding nonlinearity to a network. This helps the network to learn complex patterns. The MesResNet50 classifier head uses both Leaky ReLU and regular ReLU [20]. The regular ReLU function is defined as:

$$f(x) = \max(0, x) = \begin{cases} x, \text{ if } x > 0, \\ 0, \text{ if } x \leq 0. \end{cases} \quad (1)$$

To address the limitations of ReLU, the MesResNet50 model uses a Leaky ReLU activation function:

$$f(x) = \begin{cases} x \text{ if, } x > 0, \\ \alpha x \text{ if}, x \leq \text{b}. \end{cases} \quad (2)$$

Here, α is a small positive number ($\alpha = 0.1$). This function maintains a small gradient for negative inputs [6]. This helps neurons remain active and continue learning during training [21].

1) Regularization layers

The MesResNet50 architecture includes normalization and regularization layers for batch processing to improve the stability and generality of the model. The batch normalization layer normalizes the activations of the layers within each mini-batch. For a given mini-batch of activations $\{x1, \ldots, xm\}$, the normalization process is defined as
Calculation of the mini-batch mean:

$$\mu_B = \frac{1}{m} \sum\nolimits_{i=1}^{m} xi \quad (3)$$

Calculation of the mini-batch variance:

$$\sigma_B^2 = \frac{1}{m} \sum\nolimits_{i=1}^{m} (xi - \mu_B)^2 \quad (4)$$

Normalize activations:

$$x\hat{} = \frac{x_i - \mu B}{\sqrt{\sigma_B^2 + \varepsilon}} \quad (5)$$

$$\text{Scale and shift: } \; y_i = \gamma \, x\hat{} \; \text{i} + \beta \quad (6)$$

Table 2
Classifiers header architecture

Layer type	Output shape	Purpose	Activation function
GlobalAveragePooling2D	(None, 2048)	Down samples feature maps, reduces parameters	–
Batch Normalization	(None, 2048)	Stabilizes and accelerates training	–
Dropout(0.5)	(None, 2048)	Regularization, prevents co-adaptation	–
Dense(512)	(None, 512)	Feature learning	–
LeakyReLU(alpha = 0.1)	(None, 512)	Nonlinearity, mitigates dying ReLU problem	Leaky ReLU
Batch Normalization	(None, 512)	Stabilizes and accelerates training	–
Dropout(0.4)	(None, 512)	Regularization, prevents co-adaptation	–
Dense(256)	(None, 256)	Feature learning	ReLU
Dropout(0.3)	(None, 256)	Regularization, prevents co-adaptation	–

Here, γ and β are adjustable settings that help the network return to its original form, if required.

Classification Output:

The last layer of the classifier uses a softmax activation function [11]. For an input vector z with K dimensions (number of classes), the softmax function finds the probability of each class i as:

$$\sigma(z_i) = \frac{e^{zi}}{\sum_{j=1}^{k} e^{z\,j}} \tag{7}$$

This function ensures that the total of all class probabilities adds up to 1. This helps make clear and understandable classification decisions.

3.5. Experimental setup and implementation

Fine-tuning uses a lower learning rate for the main layers and a higher rate for the new parts. This helps maintain old knowledge while learning new MRI patterns [22]. Adding two dropout layers, batch normalization, and Leaky ReLU activation functions helps in regularization and keeps the gradients stable. The algorithm outlines the crucial steps for constructing the MesResNet50 model.

1) Start with a Foundation Model: Use a pre-trained ResNet50 model to recognize general features from a large set of images.
2) Fine-Tuning: Fine-tuning was simplified by keeping the first 20 layers of the ResNet50 model unchanged. This maintains the model's main capability to recognize features while allowing the training of deeper layers on new medical images.
3) Build a Custom Classifier: Integrate a specialized section at the end regarding the model's capability to handle the classification task. This newly incorporated head consists of multiple layers such as
   - Reducing the size of the data.
   - Stabilizing the training process.
   - Applying different levels of regularization to prevent overfitting.
4) Final Step: A new classifier head is also added to ResNet50 inthe final step to generate the final MesRes-Net50 modeland then trained with a brain tumor dataset for classification.

MesResNet50 uses transfer learning, has some of its layers frozen, and has a powerful classification head, which allows for better classification of brain tumors than other CNNs used for medical imaging [23].

The previous CNN-based medical imaging influenced the choices made when designing MesResNET50. This was done to keep from overfitting, to improve the flow of gradients, and to allow for better feature adaptation for this type of application.

3.6. Summary of comparisons

A comparison of ResNet50, AlexNet, VGG16, and a custom CNN shows their strengths and weaknesses, as shown in Table 3. ResNet50 is a deep network with approximately 25 million parameters. It is good at learning complex features, especially when it comes to medical images, but it takes longer to train and is slower to use than other models. Compared to ResNet50, AlexNet's depth spans over eight layers and nearly 60 million parameters. It is very simple and faster but can overfit, so it is better if tasks are easier. VGG16 is deeper as it has around 138 million parameters and is often used if we are using transfer learning. However, it takes more time for training time hence slow to

Table 3
Model comparisons

Feature/model	CNN (custom)	AlexNet	VGG16	ResNet50
Architecture type	Custom Lightweight CNN	Early CNN (shallow)	Deep Sequential CNN	Residual Network (deep)
Input size	Variable (e.g., 224 × 224 × 3)	227 × 227 × 3	224 × 224 × 3	224 × 224 × 3
Depth	6–10 layers (user-defined)	8 layers	16 layers	50 layers
Key layers	Conv + Pool + FC	Conv + FC Layers	Conv (3 × 3) + FC Layers	Conv + Residual Blocks
Residual blocks	Optional	No	No	Yes
Pooling	Max Pooling	Max Pooling	Max Pooling	Max Pooling
Activation	ReLU	ReLU	ReLU	ReLU
Fully connected	1–2 Dense Layers	2–3 Dense Layers	2–3 Dense Layers	1 Global Avg + Dense Layers
Normalization	BatchNorm (optional)	Local Response Norm (LRN)	No	BatchNorm in Residual Blocks
Dropout	Yes	Yes	Yes	No
Parameters (approx)	~1–5 million	~60 million	~138 million	~25.6 million
Training time	Low	Moderate	Very high	High
Overfitting risk	Moderate	High	High	Low (due to residuals)
Inference speed	Fast	Fast	Slow	Slower
Best use case	Small-scale classification	Early vision tasks	Transfer learning tasks	Complex features, medical AI

use. A custom CNN has fewer parameters (1–5 million), trains quickly, and is faster to use than a conventional CNN. It is good for small tasks but may not learn complex features, such as deeper models.

4. Experimental Results

4.1. Evaluation metrics

We evaluated the models using standard classification metrics: accuracy, precision, recall (sensitivity), F1-score, Receiver Operating Characteristic - Area Under the Curve (ROC-AUC), and confusion matrix. Accuracy measures the overall fraction of correctly classified instances and is defined as the ratio of accurate forecasts to the overall count of samples [12]. Precision (positive predictive value) is the proportion of correctly identified positive cases (TP) to all predicted positives (TP + FP), indicating the precision of the model [24]. Recall (sensitivity) is the TP divided by all actual positives (TP + FN), reflecting the model's ability to detect positive cases. The F1-score represents the harmonic mean between precision and recall, balancing the trade-off. ROC-AUC represents the region beneath the receiver operating characteristic curve, summarizing the trade-off between the true positive rate and false positive rate across thresholds. A higher AUC indicates a better discriminative power [25].

Finally, the confusion matrix tabulates the TP, FP, correctly classified negatives (TN), and missed positives (FN) for each class, revealing class-specific errors, as shown in Table 4.

4.2. Performance analysis of MesResNet50 vs. others

Table 5 shows the test-set performance of the proposed MesResNet50 related to CNN, AlexNet, VGG16, and ResNet50 across all metrics. MesResNet50 achieved the highest accuracy (0.96796), precision (0.96799), recall (0.96622), F1-score (0.96694), and ROC-AUC (0.99488). In contrast, the baseline CNN had the lowest accuracy (0.78718) and AUC (0.81092), indicating a limited separability among the classes.

AlexNet (accuracy = 0.90160, AUC = 0.97438) and VGG16 (accuracy = 0.87109, AUC = 0.94788) performed moderately, whereas ResNet50 underperformed (accuracy = 0.75439, AUC = 0.86354), likely because of over-parameterization or insufficient tuning [20]. The superiority of deeper architectures has also been observed in previous studies. Our MesResNet50 AUC (~0.995) and F1 (~0.967) are comparable to the 99.2% AUC achieved by hybrid deep CNNs in and close to the DenseNet-based classifiers reported by Nayak et al. [17].

4.3. Discussion on results

MesResNet50 achieved an ROC-AUC of 0.995, which indicates that it can perfectly separate classes. However, the F1-score of 0.967 indicates it has good precision and recall. This is important in medical tests to avoid mistakes like false negatives and false positives [26]. Compared with ResNet50, which has a lower recall (0.73588). The baseline ResNet50 did not perform well because it used standard blocks that lost detailed spatial information as they went deeper. Brain tumors normally exhibit slight intensity changes and uneven edges, which ResNet50 struggles to capture. This led to more errors in the tumor identification process, as shown in the confusion matrix. In contrast, MesResNet50 gave a better feature refinement path and multiscale representation. This helps to maintain detailed tumor information, leading to better recall, F1-score, and ROC-AUC in our tests.

MesResNet50 detects more true positives without compromising precision, which is reaffirmed by the ROC curve patterns. MesResNet50 dominates across all thresholds, whereas the CNN's lower AUC reflects weaker discrimination, as shown in the ROC curve. MesResNet50 was able to achieve ideal classification. MesResNet50 achieved an excellent AUC of 1.00, demonstrating superior performance than all other models; however, the CNN demonstrated the poorest separability, with an AUC = 0.93. While AlexNet and VGG16 both exhibited nearly perfect performances, the ResNet50 model also performed well, albeit at a lower accuracy. The strength of the model lies in the combination of the residual architecture and additional enhancements that allow for the extraction of deep features from MRI data, as previously demonstrated by Nayak et al. [17] and Srinivasan et al. [20]. Furthermore, there are no signs of early overfitting, which is indicated by the fact that the validation loss

Table 4
Definitions of evaluation metrics

Metric	Definition
Confusion matrix	Matrix of TP, FP, TN, FN counts for each class, showing misclassification patterns
Accuracy	TP + TN/total samples — Overall fraction of correct predictions
Precision	TP/(TP + FP) — Proportion of predicted positives that are correct
Recall	TP/(TP + FN) — Proportion of actual positives correctly predicted
F1-score	2 × (Precision × Recall)/(Precision + Recall) — The arithmetic average of precision and recall
ROC-AUC	Area under the ROC curve; higher values indicate stronger overall discrimination

Table 5
Performance comparison of all models

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
ResNet50	0.754 39	0.758 89	0.735 88	0.7199	0.863 54
CNN	0.787 18	0.785 72	0.771 08	0.765 94	0.810 92
VGG16	0.871 09	0.866 85	0.863 74	0.860 76	0.947 88
AlexNet	0.9016	0.907 31	0.894 05	0.896 01	0.974 38
MesResNet50	0.967 96	0.967 99	0.966 22	0.966 94	0.994 88

and training loss remain closely aligned. However, due to the high degree of complexity associated with MesResNet50, this model will require larger amounts of computing power.

As noted by Ullah et al. [19], deeper networks require large datasets, hypothetically limiting real-time or low-resource deployment. While our dataset softens overfitting risks, smaller datasets could be problematic.

The line plot in Figure 3(b) presents the results of the evaluations using the following five criteria (accuracy, precision, recall, F1-score, and ROC-AUC) for the CNN, AlexNet, VGG16, ResNet50, and MesResNet50 models. The MesResNet50 model exhibited the highest performance in each of the five evaluation metrics. MesResNet50 had an accuracy, precision, recall, and F1-score of approximately 0.97, as well as an ROC-AUC of 1.00; this is indicative that the MesResNet50 model can classify tumors with nearly perfect dependability.

MesResNet50 outperformed all the other models based on all the evaluation measures. Although VGG16 and AlexNet could produce reasonable results, CNN had the lowest total performance of any model evaluated. The consistently large performance difference measured by the models demonstrates a clear ranking order of the models. The confusion matrices illustrated in Figure 4 demonstrate the differences in how each model classified the tumors. The classifications made by MesResNet50 were extremely accurate, with minimal misclassifications; however, both CNN and ResNet50 struggled to separate some tumor types

Figure 3
(a) Combined ROC curve of all models. (b) Inline plot of all metric parameters

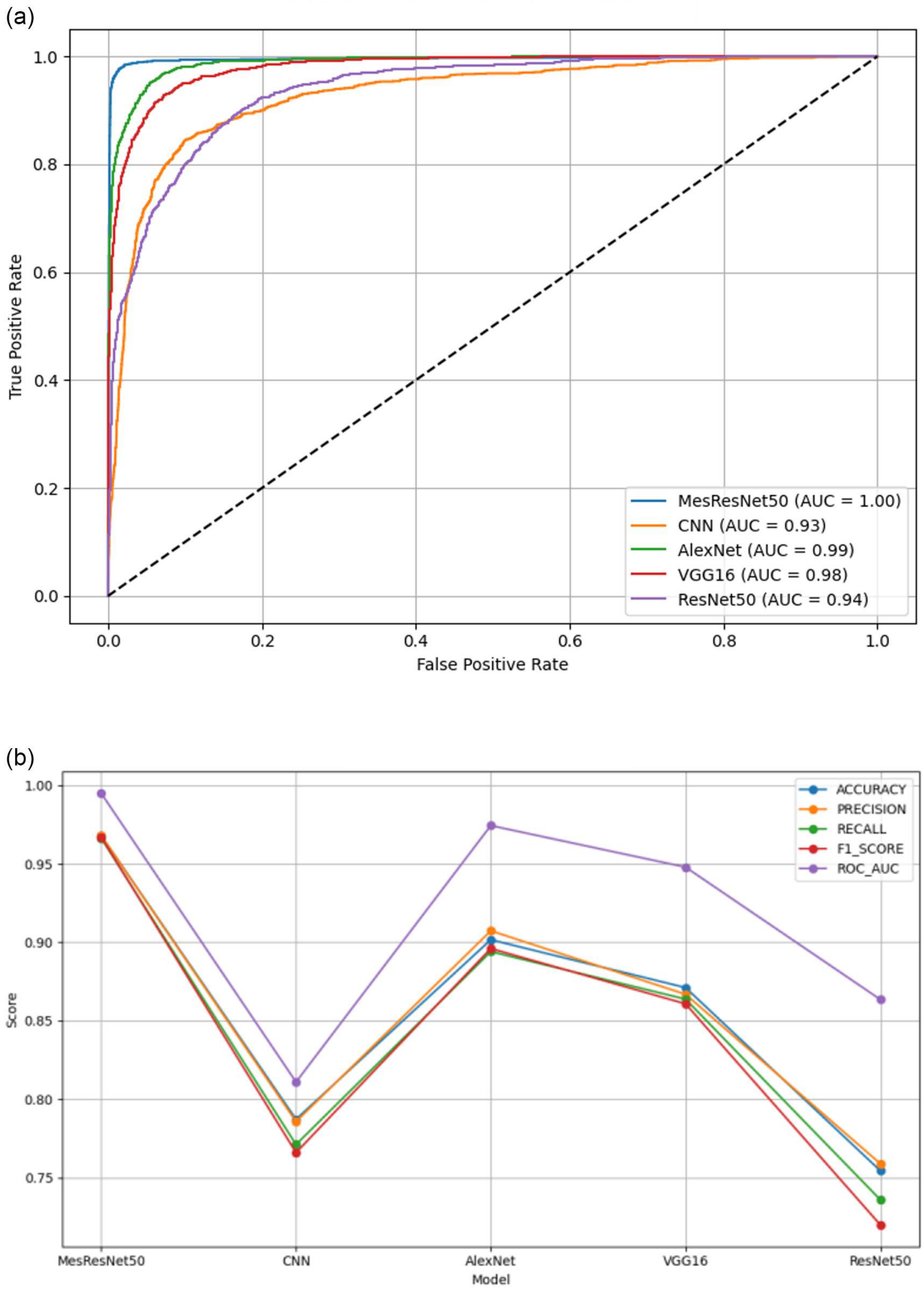
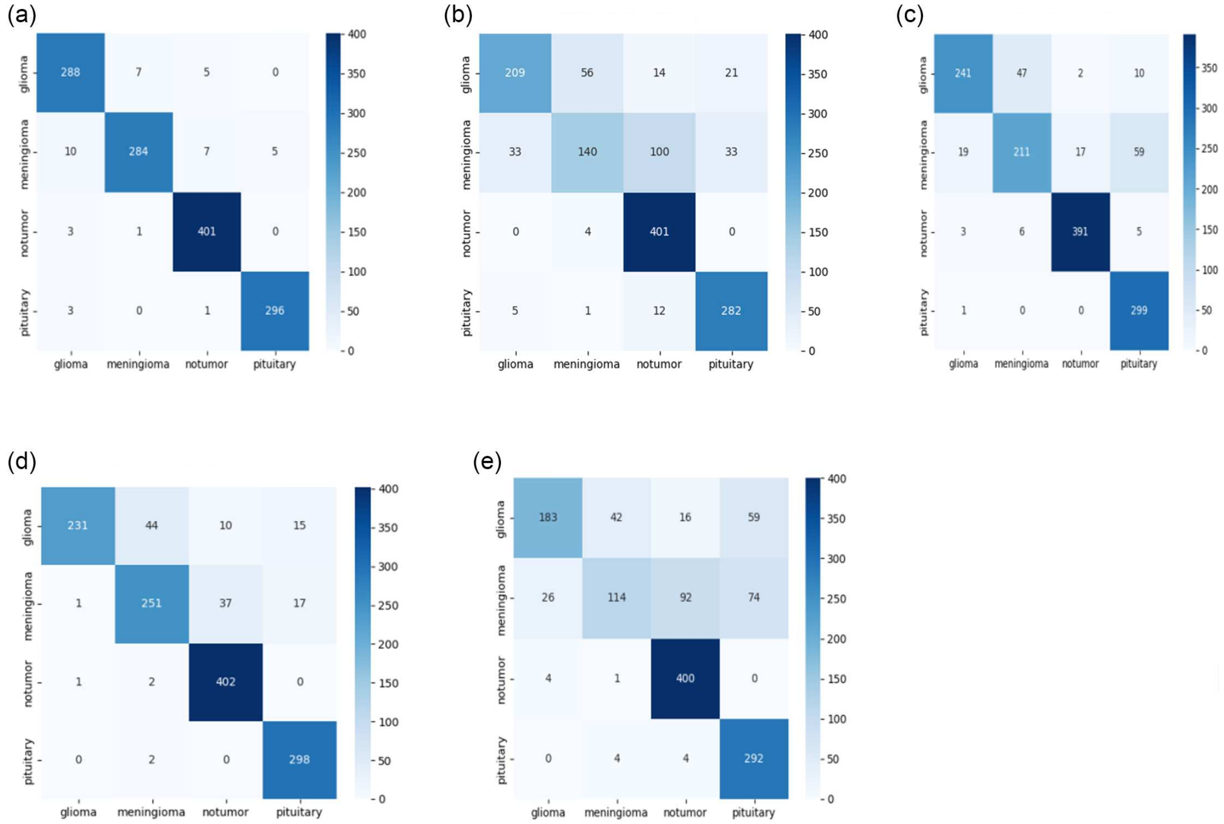


Figure 4
Confusion matrix of all the models: (a) mesResnet50, (b) CNN, (c) VGG16, (d) AlexNet, and (e) Resnet50



and thus had numerous misclassifications [15]. AlexNet had a middle-ground performance and was, therefore, more prone to creating false positives. VGG16 yielded a somewhat balanced outcome; however, it too suffered from class overlap. In addition to the superior metrics, MesResNet50 also had a greater ability to generalize. Thus, future research should focus on reducing the computational load through pruning.

MesResNet50 demonstrated improvements in precision, F1-score, and ROC-AUC [17, 18], establishing it as a potential contender for brain tumor classification.

5. Conclusion

This research developed and tested MesResNet50 as a new method to classify different types of brain tumors by applying deep learning techniques to MRIs. MesResNet50 surpassed benchmarks (CNN, AlexNet, VGG16, and ResNet50) with respect to its ability to accurately perform on each of the evaluation criteria based upon a set of 7023 images from four tumor categories.

The model achieved an accuracy on the test data of 96.80%, an F1-score of 96.69% as well as an ROC-AUC of 0.9949, clearly showing that it was able to show superior discrimination along with a good balance of sensitivity and specificity performance. The discrimination and sensitivity/specificity performance capabilities of MesResNet50 are due to the residual nature of the model and also the capability of extracting features to a greater depth than other models and improving generalized ability based on current trends of research in deep learning. However, as with most improvements in performance, there is a trade-off for additional computation requirements, which may be a limitation in resource-constrained environments.

Overall, this study has demonstrated that MesResNet50 is capable of providing an accurate, reliable method for automated diagnosis of brain tumors in clinical practice and decision making; additionally, there are opportunities for future studies to continue to improve the architectures for real-time inference, to develop even lighter-weight model versions for the same, and to test the validity of these models using multi-institutional datasets so that they can be applied broadly across multiple institutions and by clinicians.

Future work is intended to develop a version of MesResNet50 that has a greater level of speed and to evaluate its robustness and reliability at multiple locations. Compression methods for models, like knowledge distillation and network pruning, could be used to reduce computational cost without losing performance. Possibly simpler design patterns, or combinations of CNN and Transformer Blocks, could also increase performance. Evaluating the model on MR images acquired from a variety of sites would help with adapting to the problem of domain shift using methods of data normalization, style transfer, and data augmentation. More advanced methods (i.e., elastic deformation of images and generating synthetic MRIs) will enable the model to adapt to different scanner manufacturers' equipment so that it is useful for clinical use.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The Brain Tumor MRI datasets that support the findings of this study are openly available in Kaggle at https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset. The data that support the findings of this study are openly available in GitHub at https://github.com/vasanthbhagawat-source/Ensembled.git.

Author Contribution Statement

Vasanth C. Bhagawat: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Pravinth Raja Suthkar:** Validation, Resources, Supervision, Project administration.

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