Jurnal ELTIKOM :
Jurnal Teknik Elektro, Teknologi Informasi dan Komputer

Vol. 10, No. 1, June 2026, page. 77-87
ISSN 2598-3245 (Print), ISSN 2598-3288 (Online)
DOI: http://doi.org/10.31961/eltikom.v10i1.1894
Available online at http://eltikom.poliban.ac.id

LIGHTWEIGHT MULTI-MODEL CNN FUSION OF RESNET50V2 AND MOBILENETV2 FOR ACCURATE BRAIN TUMOR CLASSIFICATION ON MRI SCANS

Abd Salam At Taqwa[1*], Muhammad Fadhlullah[1], La Ode Fefli Yarlin[2]
[1)] Department of Informatics and Computer Engineering, State University of Makassar, Makassar, Indonesia
[2)] Department of Informatics, Mega Buana University, Palopo, Indonesia
e-mail: abd.salam.attaqwa@unm.ac.id, muh.fadhlullah@unm.ac.id, fefli-yarlin@umegabuana.ac.id

Received: 25 August 2025 – Revised: 4 April 2026 – Accepted: 13 April 2026

ABSTRACT

Brain tumor classification remains a critical challenge in medical imaging because manual diagnosis from Magnetic Resonance Imaging is time-consuming and may produce inconsistent interpretations. Automated approaches using deep learning have shown promising results, although single-model methods may still face limitations in generalization and stability. This study introduces a lightweight multi model Convolutional Neural Network that combines MobileNetV2 and ResNet50V2 as dual-backbone feature extractors. MobileNetV2 supports computational efficiency, while ResNet50V2 strengthens residual feature learning. The Bangladesh Brain MRI Dataset, which contains 6,056 images in three categories, Brain Glioma, Brain Meningioma, and Brain Tumor, was used in this study. All images were resized to 224 × 224 pixels before feature extraction, fusion, and classification. The proposed multi-model achieved 99.56% training accuracy and 93.37% validation accuracy, outperforming MobileNetV2 with 98.37% and 89.60 percent, and ResNet50V2 with 97.55% and 86.17 percent. On the test set, it reached 94.89% accuracy, 0.1536 loss, and 0.991 ROC AUC. These results show that integrating lightweight and deep architectures can improve robustness and accuracy while maintaining efficiency, making this approach suitable for real-world clinical support in brain tumor diagnosis.

Keywords: *brain tumor classification, MobileNetV2, MRI, multi-model CNN, ResNet50V2.*

I. INTRODUCTION

BRAIN tumors are a major concern in neurological disorders, where timely and accurate diagnosis is essential for improving survival rates and treatment planning. Magnetic Resonance Imaging (MRI) is widely used as a standard diagnostic tool because it provides high spatial resolution and detailed anatomical structures without ionizing radiation [1]. However, manual interpretation of MRI scans is often time-consuming and subject to observer variability, which supports the need for automated methods. With recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), automated brain tumor classification systems have shown strong potential to improve diagnostic reliability and efficiency [2], [3].

Advancements in Convolutional Neural Networks (CNNs) and transfer learning have also improved classification performance in MRI-based tumor detection. Pretrained architectures such as DenseNet121 [4], ResNet50 [5], MobileNetV2 [6], InceptionResNetV2 [7], and EfficientNet [8] have been widely used for feature extraction from large-scale datasets such as ImageNet. Putri et al. [9] achieved 98.44% accuracy using ResNet50, outperforming DenseNet121, while Somoal and Dzikrillah [10] reported 98% accuracy with MobileNetV2 using the Adam optimizer and transfer learning. Optimization and augmentation strategies have further improved performance. For example, Mahendra et al. [11] reached 99.70% accuracy with InceptionResNetV2 and MixUp augmentation, and Kurniawan and Utami [12] found that VGG16 delivered 94.93% accuracy despite shorter training times. Similar gains have been observed with MobileNetV2 [13], SVM optimization [14], and CNN-based early detection [15].

Ensemble and hybrid approaches have shown further improvements. Hosny et al. [16] combined DenseNet121 and InceptionV3 to achieve 99.02% accuracy, while Mathivanan et al. [17] introduced the Brain-Tumor Detection Network (BTDN), reaching 99.68% accuracy. Pande and Chaki [18] combined DenseNet121 and ResNet101 with PCA and Random Forest to maintain over 90% accuracy on noisy data, and Abdusalomov et al. [19] adapted MobileNet into RetinaNet for lightweight deployment. Feature engineering methods have also produced strong results, including FlexiCombFE by Tuncer et al. [20] with 99.35% accuracy and hybrid attention AlexNet by Chaudhary et al. [21] with 99.69% accuracy, have also shown strong results. Architectural improvements like those by Ishaq et al. [22] on EfficientNet and Sharma et al. [23] on ResNet50 further demonstrate the value of customized deep learning designs.

Comparative studies underline the benefits of transfer learning and data augmentation. Anaya-Isaza et al. [24] found that transfer learning with augmented datasets improved accuracy by up to 6%, while Disci et al. [25] reported Xception as the top-performing model at 98.73% accuracy. Hybrid CNN–machine learning combinations have also emerged, with Shoaib et al. [26] combining DenseNet201 features with SVM and MLP classifiers to achieve up to 100% accuracy, and İncir and Bozkurt [27] attaining 98.41% accuracy through EfficientNetV2-M and InceptionV3 concatenation. Large-scale evaluations confirm that transfer learning remains important for improving accuracy while reducing computational cost [28], [29], [30], [31], [32]. Taken together, these findings suggest that multi-model integration, lightweight architectures, advanced feature engineering, and transfer learning are promising directions for accurate, efficient, and clinically viable brain tumor classification.

Despite these advancements, most existing studies focus on either lightweight architectures or deep residual networks but rarely combine the two to achieve both computational efficiency and high accuracy. Furthermore, although ensemble learning has been explored, lightweight multi-model fusion for resource-limited clinical environments remains underrepresented in the literature. This study addresses this gap by proposing a lightweight multi-model CNN fusion of MobileNetV2 [6] and ResNet50V2 [33] for brain tumor classification from MRI scans. MobileNetV2 provides computational efficiency for real-time applications, while ResNet50V2 offers deep residual learning for complex feature representation. The contributions of this work include (1) developing a hybrid CNN fusion that integrates a lightweight and a deep architecture, (2) optimizing the architecture for minimal computational overhead without sacrificing accuracy, and (3) evaluating the proposed model on the Bangladesh Brain Cancer MRI Dataset, consisting of 6,056 labeled images across three tumor types: Brain Glioma, Brain Meningioma, and Brain Tumor (general). The proposed approach is expected to achieve high classification performance while remaining practical for deployment in clinical and low-resource settings.

II. RESEARCH METHOD

This study adopts a systematic approach to improving brain tumor classification accuracy using MRI images. The method is structured into several key stages: data collection, image preprocessing, model design, training, and performance evaluation. A multi-model architecture combining MobileNetV2 and ResNet50V2 is used to draw on the strengths of both lightweight and deep CNN models. Each stage is described in detail in the following subsections.

A. Data Collection

This study uses the Brain Cancer MRI dataset developed by Rahman [34], a curated collection of brain MRI images designed to support medical diagnostic research, particularly the detection and classification of brain tumors. The dataset consists of a total of 6,056 MRI images grouped into three main classes: Brain Glioma with 2,004 images, Brain Meningioma with 2,004 images, and Brain Tumor (general) with 2,048 images. Figure 1 presents sample images from the dataset used in this study. All images were obtained from several hospitals in Bangladesh through collaboration with experienced medical professionals to ensure accurate labeling and diverse case representation. Each image was uniformly resized to 512 × 512 pixels to maintain consistency and compatibility with image processing techniques, machine learning algorithms, and deep learning models. The availability of this dataset is particularly valuable because high-quality medical imaging data for brain tumor cases remain limited, especially in developing regions. Therefore, this dataset provides a reliable foundation for developing and evaluating artificial intelligence-based diagnostic systems.

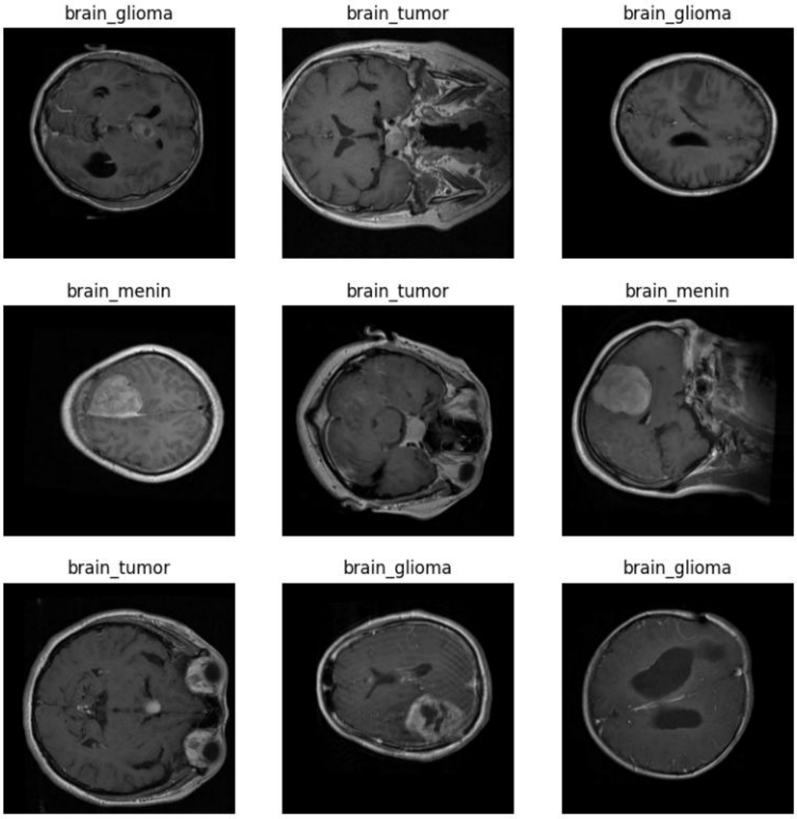


Figure 1. Brain Cancer MRI Dataset

B. Image Preprocessing

All data preprocessing procedures in this study were conducted using the latest version of the TensorFlow framework. The primary objective of this stage was to prepare the image data according to the input specifications of deep learning models and to improve the model's generalization performance.

1) Image Resizing and Format Adjustment

The original MRI images were uniformly resized to 224 × 224 pixels to ensure compatibility with contemporary convolutional neural network architectures. Although the source scans were typically grayscale, all images were converted to RGB format with three color channels so that they matched the input dimensionality expected by the pretrained models used in this study. This step standardizes spatial resolution and channel structure across the entire dataset.

2) Normalization and Batch Processing

After resizing and format conversion, pixel intensities were scaled to the [0, 1] range by dividing each value by 255. This normalization reduces numeric instability and accelerates convergence during training. The data were organized into mini-batches of 32 to balance computational efficiency with stable gradient updates, supporting effective optimization of the model parameters.

3) Dataset Splitting

The dataset was divided into three separate portions: 75% for training, 15% for validation, and 15% for testing. The split was performed while maintaining class balance so that each subset reflected the overall distribution of the categories. The training portion was used to fit the model, the validation portion was used to monitor performance and adjust hyperparameters, and the testing portion was reserved for an independent evaluation of the final model.

4) Data Augmentation

Real-time data augmentation was applied only to the training subset to increase the effective dataset size, improve diversity, and strengthen the model's generalization capability. The augmentation procedures included horizontal and vertical flipping to represent variations in spatial orientation, random rotations of up to ±20% to introduce orientation variability, and random zoom operations of up to ±20% to simulate scale differences. No augmentation was applied to the validation or testing subsets, ensuring the consistency and integrity of model performance evaluation.

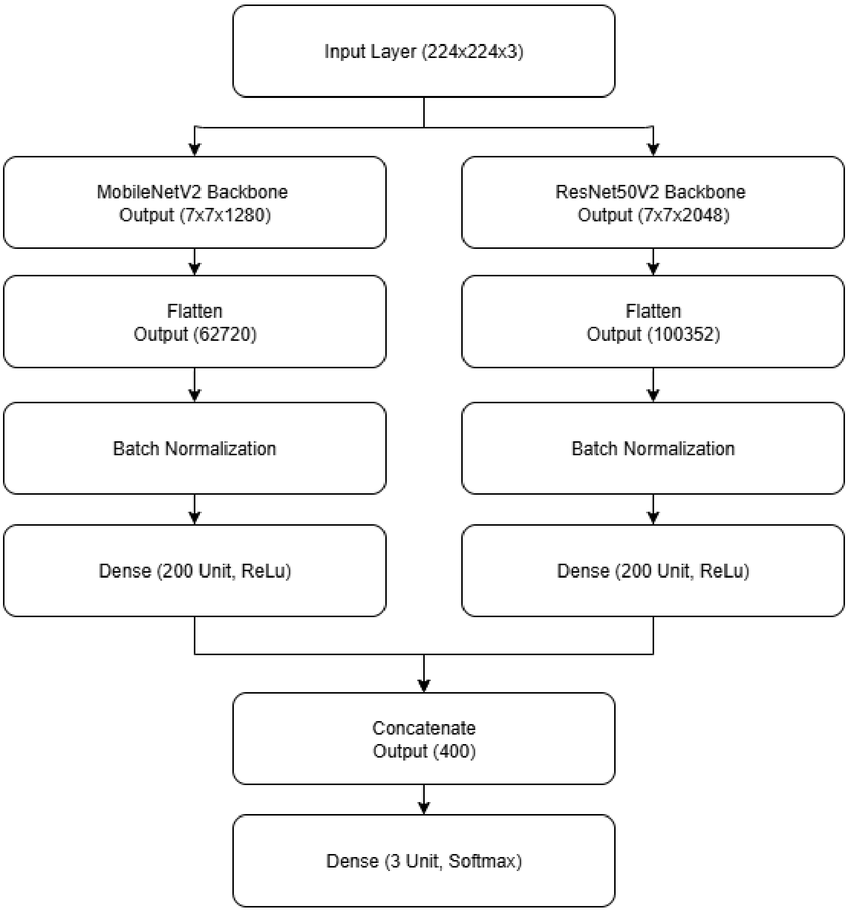


Figure 2. Architectural Overview of the Proposed Brain MRI Classification System

C. Model Architecture

The model used in this study adopts a multi-backbone convolutional neural network architecture that integrates two pretrained models, MobileNetV2 and ResNet50V2, both initialized with weights from ImageNet training. This dual-backbone design is intended to use the complementary strengths of each model in extracting discriminative visual features from brain MRI images. By combining the lightweight and efficient feature extraction capabilities of MobileNetV2 with the deeper and more complex representations learned by ResNet50V2, the architecture aims to produce a more comprehensive and robust feature representation for classification. Figure 2 illustrates the proposed model architecture, including the dual-backbone structure, intermediate processing layers, and final classification layer.

The developed model takes MRI images as input, each resized to 224 × 224 pixels with three RGB channels. The architecture uses a dual-backbone framework that combines two pretrained convolutional neural networks to draw on their complementary capabilities in feature representation.

1) Backbone Feature Extractors

The input images are processed simultaneously by two pretrained models: MobileNetV2, which serves as a lightweight feature extractor with high computational efficiency, and ResNet50V2, which captures deeper and more complex representations through residual connections. Both backbones are initialized in non-trainable mode, with frozen weights, to preserve the pretrained feature representations, and their original fully connected layers are excluded.

2) Feature Flattening and Normalization

The output feature maps from each backbone are transformed into one-dimensional vectors using a Flatten layer. These vectors are then normalized using Batch Normalization to accelerate convergence and stabilize the training process.

3) Dense Transformation and Feature Fusion

Each normalized feature vector is passed through a Dense layer with 200 neurons and ReLU activation to apply non-linear transformations. The outputs from both Dense layers are then concatenated to produce a unified feature vector that combines the representational strengths of both backbones.

4) Final Classification Layer

The combined feature representation is directed to a fully connected layer containing three nodes, aligned with the classification labels. A Softmax activation is then applied at the output stage to determine the likelihood of each class.

This architecture combines the computational efficiency of MobileNetV2 with the representational depth of ResNet50V2. By integrating features from both networks through an ensemble-like approach, the model improves classification performance for brain tumor detection in MRI images, aligning with findings from prior studies in medical imaging.

D. Model Training

The training process in this study was designed to optimize model performance while minimizing overfitting and maintaining computational efficiency. Key hyperparameters, including learning rate, batch size, number of epochs, and optimizer, were determined through preliminary experiments to balance convergence speed and stability. An early stopping strategy was applied by monitoring validation accuracy with a patience value of 10 and a minimum improvement requirement of 0.2, as well as validation loss with a patience value of 5 and a minimum reduction requirement of 0.05. This approach supports optimal performance while preventing overfitting when using high-capacity architectures such as the combination of MobileNetV2 and Res-Net50V2.

E. Evaluation Metrics

To measure effectiveness, the model was tested using widely recognized metrics, including accuracy, loss, precision, recall, F1 score, ROC AUC, and confusion matrix. Independent validation data ensured that the evaluation remained objective and unbiased. The selected metrics provided a broad view of performance by accounting for overall accuracy, error rate, class sensitivity, and the relationship between precision and recall. ROC AUC and the confusion matrix also provided further insight into discrimination power and per-class outcomes. In addition to predictive performance, computational complexity was analyzed by examining the number of parameters and inference time of each model, allowing the efficiency of the proposed architecture and its feasibility for practical deployment in medical imaging applications to be assessed.

III. RESULTS AND DISCUSSION

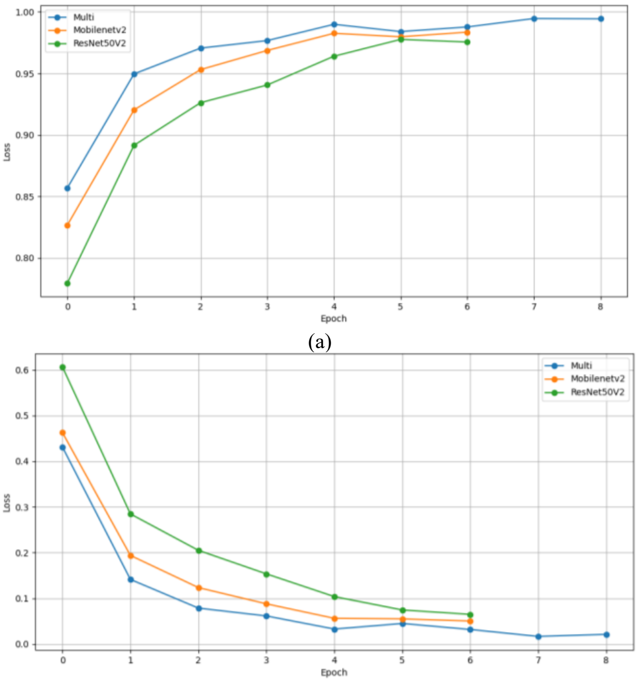
In this section, we present and analyze the results of the brain tumor classification models, focusing on MobileNetV2, ResNet50V2, and the proposed multi-model approach that combines both architectures. The analysis covers two main aspects: model convergence and stability, as well as performance metrics, including accuracy, loss, precision, recall, F1-score, ROC AUC, and confusion matrices. Detailed insights and comparative discussion are provided in the following subsections, highlighting the strengths and limitations of each model in producing accurate and reliable classification results on MRI brain scan data.

A. Analysis of Accuracy and Loss on Training and Validation Data

This section provides a detailed analysis of the model learning process by examining the accuracy and loss curves on both the training and validation datasets. The primary goal is to evaluate model convergence and identify any signs of overfitting or underfitting throughout the training epochs.

Figure 3 illustrates the training accuracy and loss curves for MultiModel, MobileNetV2, and ResNet50V2. The accuracy trends in Figure 3(a) show that all models improve consistently, with MultiModel achieving the highest accuracy throughout training, followed by MobileNetV2 and ResNet50V2. The loss curves in Figure 3(b) indicate that MultiModel consistently records the lowest loss, reflecting a better fit to the training data. These results suggest that combining MobileNetV2 and ResNet50V2 in a multi-model architecture improves convergence and classification performance compared with the individual models.

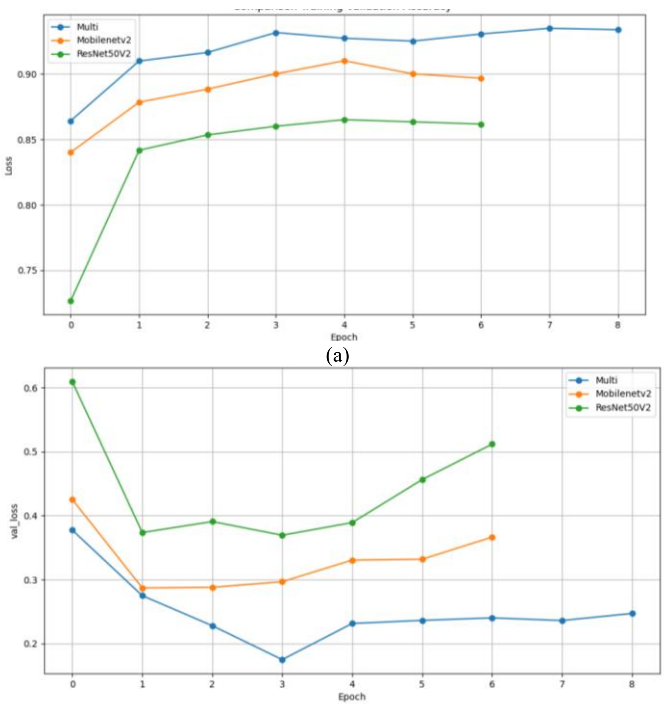
Figure 4 presents the validation accuracy and loss curves for MultiModel, MobileNetV2, and ResNet50V2. As shown in Figure 4(a), MultiModel consistently outperforms the other models in validation accuracy across all epochs, followed by MobileNetV2, while ResNet50V2 records the lowest accuracy. The validation loss curves in Figure 4(b) indicate that MultiModel maintains the lowest and most stable loss throughout training, suggesting better generalization and a lower risk of overfitting. These results



(a)

(b)

Figure 3. Training Performance Metrics: (a) Training Accuracy and (b) Training Loss



(a)

(b)

Figure 4. Validation Performance Metrics: (a) Validation Accuracy and (b) Validation Loss

confirm that the fusion of MobileNetV2 and ResNet50V2 provides better validation performance than using each backbone independently.

As shown in Table 1, the Combined (Multi) model achieved the highest training accuracy at 99.56% and validation accuracy at 93.37%, surpassing the individual performances of MobileNetV2 and ResNet50V2. MobileNetV2 recorded a training accuracy of 98.37% and a validation accuracy of 89.60%, while ResNet50V2 achieved 97.55% and 86.17%, respectively. These results indicate that integrating MobileNetV2 and ResNet50V2 improves feature representation, allowing the Combined model to generalize more effectively to unseen data. In addition, the smaller gap between training and validation

TABLE 1
TRAINING ACCURACY RESULTS

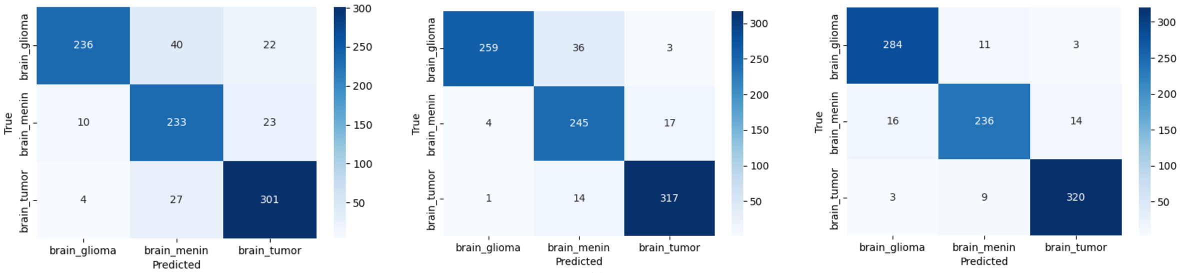
Model	Training Accuracy	Validation Accuracy
ResNet50V2	97.55%	86.17%
MobileNetV2	98.37%	89.60%
Combined (Multi)	**99.56%**	**93.37%**

TABLE 2
COMPARISON OF ACCURACY AND LOSS ON TEST DATA

Model	Training Accuracy	Validation Accuracy
ResNet50V2	84.83	0.3746
MobileNetV2	92.60	0.2374
Combined (Multi)	**94.89**	**0.1536**

TABLE 3
SUMMARY OF CLASSIFICATION EVALUATION METRICS

Model	Precision	Recall	F1-Score	ROC AUC
ResNet50V2	0.86	0.86	0.86	0.967
MobileNetV2	0.92	0.91	0.92	0.983
Combined (Multi)	**0.94**	**0.93**	**0.94**	**0.991**



(a) (b) (c)

Figure 5. Confusion Matrices of the Models: (a) ResNet50V2, (b) MobileNetV2, and (c) Multimodel

accuracy in the Combined model suggests better stability and reduced overfitting compared with the standalone architectures.

B. Comparison of Performance on Test Data

This section evaluates the generalization performance of the trained models using the unseen test dataset. The analysis compares accuracy and loss values to identify which architecture provides the most robust and reliable classification capability.

As shown in Table 2, the Combined (Multi) model achieved the best performance, with a test accuracy of 94.89% and the lowest loss of 0.1536, outperforming both MobileNetV2 and ResNet50V2. This finding shows that combining the two architectures improves classification accuracy and reduces prediction error compared with using either model individually. However, because the proposed model was evaluated on a single dataset, its generalization across different clinical environments may still be limited.

C. Evaluation Based on Classification Metrics

Beyond overall accuracy, per-class performance evaluation provides a deeper understanding of model behavior. This analysis uses key classification metrics, including precision, recall, F1-score, and ROC AUC, to assess the models' ability to handle each brain tumor category.

According to Table 3, the Multi-model configuration delivered better results than MobileNetV2 and ResNet50V2 across precision, recall, F1-score, and ROC AUC. With scores of 0.94 for precision, 0.93 for recall, and 0.94 for F1, along with a ROC AUC of 0.991, the model was more effective in supporting accurate brain tumor classification. The improvements in F1-score and ROC AUC show the strength of the combined approach in producing reliable predictions while reducing misclassification errors.

D. Analysis of Confusion Matrix

A detailed examination of the confusion matrix for each model is presented, providing a visual and numerical representation of classification performance. This analysis reviews the counts of true positives, false positives, and false negatives to identify the types of errors made by the models.

Based on the confusion matrices and their summary in Table 4, the final analysis confirms that the Multimodel approach provides the most effective classification performance. As shown in Figure 5,

TABLE 4
SUMMARY OF CONFUSION MATRIX (CORRECT CLASSIFICATIONS / TOTAL)

Class	ResNet50V2	MobileNetV2	Multimodel
Brain Glioma	236 / 298	259 / 298	**284 / 298**
Brain Menin	233 / 266	**245 / 266**	236 / 266
Brain Tumor	301 / 332	317 / 332	**320 / 332**

TABLE 5
COMPUTATIONAL COMPLEXITY AND INFERENCE TIME COMPARISON

Model	Total Parameters	Inference Time (ms/image)
MobileNetV2	2,257,984	42
ResNet50V2	24,812,395	64
Proposed Fusion Model	27,851,019	98

which presents the confusion matrices for ResNet50V2, MobileNetV2, and Multimodel, the Multimodel consistently achieves the highest number of correct predictions and the lowest number of misclassifications across the three tumor classes. This pattern is especially clear in the classification of Brain Glioma and Brain Tumor, where it outperforms both MobileNetV2 and ResNet50V2. Although MobileNetV2 shows strong performance and slightly surpasses the Multimodel for the Brain Menin class in the summary table, its overall performance is less consistent across all classes compared with the Multimodel. In contrast, ResNet50V2 shows the weakest performance, with a higher rate of misclassification, especially for Brain Glioma. Therefore, the combined analysis indicates that the Multimodel's fusion of features from both architectures leads to a more accurate and stable classification system.

E. Computational Complexity Analysis

In addition to evaluating classification performance, this study also analyzes the computational efficiency of the proposed architecture. Because this study claims a lightweight-oriented fusion model, a quantitative comparison of computational complexity was conducted. The analysis focuses on the total number of parameters, the number of trainable parameters, and the inference time required to process a single MRI image. These metrics provide insight into the computational cost and practical feasibility of deploying the model in real-world clinical environments. Inference time was measured during the prediction stage and represents the average time required to process one image using the same hardware configuration. The comparison between MobileNetV2, ResNet50V2, and the proposed fusion model is presented in Table 5.

As shown in Table 5, MobileNetV2 has the smallest architecture with the fastest inference time of 42 ms per image, reflecting its lightweight design. ResNet50V2 has a larger architecture with 24.81 million parameters and requires 64 ms per image. The proposed fusion model combines both architectures, resulting in 27.85 mil-lion parameters and an inference time of 98 ms per image. Although the computational cost increases, the inference time remains below 100 ms per image, indicating that the model maintains reasonable efficiency while improving classification performance. Although the proposed fusion model combines two backbone networks, its computational complexity remains manageable compared with many recent ensemble architectures that often exceed 50 to 100 million parameters. Therefore, the model retains a relatively lightweight characteristic for practical deployment.

F. Discussion and Interpretation of Results

The results of this study show that the proposed multi-model architecture, which combines MobileNetV2 and ResNet50V2, consistently outperforms the individual backbone models across all evaluation stages. Recent studies such as Hosny et al. [16] and Mathivanan et al. [17] have explored ensemble-based CNN architectures for brain tumor classification. Compared with these approaches, the proposed model emphasizes a balance between classification performance and computational efficiency. In terms of training performance (Table 1), the Combined model achieved the highest training accuracy of 99.56% and validation accuracy of 93.37%, indicating stronger feature extraction and generalization capability. The difference between training accuracy and validation accuracy suggests a moderate degree of overfitting, which is common in medical imaging datasets with limited variability. Data augmentation and early stopping were used to mitigate this effect. The relatively smaller gap between training and validation accuracy further suggests better stability and lower overfitting risk compared with standalone architectures. When evaluated on unseen test data (Table 2), the Combined model maintained its superiority with the highest accuracy of 94.89% and the lowest loss value of 0.1536, outperforming

MobileNetV2 (92.60%, 0.2374) and ResNet50V2 (84.83%, 0.3746). This finding confirms that integrating the two architectures improves classification robustness and reduces prediction error.

Further evaluation using classification metrics (Table 3) reinforces these observations. The Combined model achieved the highest precision (0.94), recall (0.93), F1-score (0.94), and ROC AUC (0.991), reflecting its strong ability to classify MRI brain tumor images correctly while minimizing both false positives and false negatives. The improvements in F1-score and ROC AUC highlight the balanced and reliable performance of the multi-model approach across different tumor types.

The confusion matrix analysis (Figure 5) provides deeper insights into class-specific performance. The Combined model recorded the highest number of correct classifications in Brain Glioma (284/298) and Brain Tumor (320/332), with a consistently lower misclassification rate than the other models. Although MobileNetV2 slightly outperformed the Combined model in the Brain Menin class, its performance was less consistent across all categories. In contrast, ResNet50V2 showed the weakest results, with more frequent misclassifications, particularly in Brain Glioma cases. Taken together, these findings confirm that the fusion of MobileNetV2 and ResNet50V2 uses the computational efficiency of MobileNetV2 and the deep representational power of ResNet50V2, resulting in a more accurate, stable, and generalizable classification framework for brain tumor detection on MRI scans. The improvement observed in the proposed model can be explained by the complementary characteristics of the two backbones. MobileNetV2 employs depthwise separable convolutions that efficiently capture local spatial patterns with low computational cost, while ResNet50V2 uses deep residual connections to learn more complex hierarchical features. The fusion layer integrates both representations, allowing the classifier to benefit from efficient low-level features and deeper semantic information at the same time.

IV. CONCLUSION

This study proposed a lightweight multi-model convolutional neural network that integrates MobileNetV2 and ResNet50V2 for brain tumor classification using MRI scans. The experimental results show that the proposed model consistently outperformed the individual backbone models, achieving a training accuracy of 99.56%, validation accuracy of 93.37%, and test accuracy of 94.89% with a loss value of 0.1536. The model also achieved strong classification performance, with a precision of 0.94, recall of 0.93, F1-score of 0.94, and ROC AUC of 0.991, indicating reliable and balanced predictions across tumor classes. The fusion of MobileNetV2's computational efficiency and ResNet50V2's deep feature extraction capability allows the model to capture complementary feature representations, resulting in improved classification performance. However, the gap between training and validation accuracy indicates mild overfitting, which was partly mitigated using data augmentation and early stopping. Additional regularization techniques, such as Dropout or L2 weight regularization, may further improve the model's generalization ability.

This study also has several limitations. The evaluation was conducted on a single dataset, and k-fold cross-validation and statistical significance testing were not included due to computational constraints. Future research should address these limitations by incorporating cross-validation strategies, statistical validation, and evaluation on additional public MRI datasets to improve the robustness and generalization of the proposed approach.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the authors used ChatGPT in order to assist with the initial brainstorming process, specifically to explore related literature and identify relevant research directions, as well as to support preliminary discussion of methods and results. After using this tool/service, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Abd Salam At Taqwa: Conceptualization, Methodology, Software, Investigation, Visualization, Writing – original draft, and Writing – review & editing. **Muhammad Fadhlullah**: Data curation, Formal Analysis, Resources, Validation and Writing – review & editing. **La Ode Fefli Yarlin**: Conceptualization, Supervision, Validation, Resources, and Writing – review & editing.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

[1] S. Bauer, R. Wiest, L.-P. Nolte, and M. Reyes, "A survey of MRI-based medical image analysis for brain tumor studies," *Phys. Med. Biol.*, vol. 58, no. 13, pp. R97–R129, 2013.

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

[3] A. Hosny, C. Parmar, J. Quackenbush, L. H. Schwartz, and H. J. W. L. Aerts, "Artificial intelligence in radiology," *Nat. Rev. Cancer*, vol. 18, no. 8, pp. 500–510, 2018.

[4] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017, pp. 4700–4708.

[5] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.

[6] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "Mobilenetv2: Inverted residuals and linear bottlenecks," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2018, pp. 4510–4520.

[7] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. Alemi, "Inception-v4, inception-resnet and the impact of residual connections on learning," in *Proceedings of the AAAI conference on artificial intelligence*, 2017.

[8] M. Tan and Q. Le, "Efficientnet: Rethinking model scaling for convolutional neural networks," in *International conference on machine learning*, PMLR, 2019, pp. 6105–6114.

[9] F. A. P. R. Putri, J. P. Tanjung, and N. P. Dharshini, "Implementation of transfer learning on cnn using densenet121 and resnet50 for brain tumor classification," *J. Informatics Telecommun. Eng.*, vol. 8, no. 2, pp. 325–334, 2025.

[10] M. G. Somoal and A. R. Dzikrillah, "Komparasi MobileNETV2 dengan Kustomisasi Transfer Learning dan Hyperparameter untuk Identifikasi Tumor Otak," *J. Teknol. Inf. dan Ilmu Komput.*, vol. 12, no. 1, pp. 229–240, 2025.

[11] R. Mahendra, E. A. Laksana, and S. Sukenda, "Pendekatan Transfer Learning dengan InceptionResNetV2 dan Augmentasi MixUp untuk Peningkatan Klasifikasi Tumor Otak," *J. Algoritm.*, vol. 22, no. 1, pp. 161–172, 2025.

[12] M. B. Kurniawan and E. Utami, "Performance Comparison of ResNet50, VGG16, and MobileNetV2 for Brain Tumor Classification on MRI Images," *Sist. J. Sist. Inf.*, vol. 14, no. 2, pp. 767–777, 2025.

[13] R. R. S. Putra, A. Sobri, and D. Nurdiansyah, "Deteksi Tumor Otak Menggunakan Citra MRI (Magnetic Resonance Imaging) Melalui Pendekatan Deep Convolutional Neural Network," *JUSIM (Jurnal Sist. Inf. Musirawas)*, vol. 10, no. 1, pp. 35–44, 2025.

[14] B. D. Irawan, R. Kurniawan, and Y. A. Wijaya, "Optimalisasi Model Klasifikasi Menggunakan Algoritma Support Vector Machine Pada Citra Brain Tumor," *JATI (Jurnal Mhs. Tek. Inform.*, vol. 9, no. 2, pp. 3493–3500, 2025.

[15] A. Sitohang, A. Sembiring, and S. Simanjorang, "Implementasi Jaringan Syaraf Tiruan Dalam Klasifikasi Citra Medis," *J. SAINTIKOM (Jurnal Sains Manaj. Inform. dan Komputer)*, vol. 24, no. 1, pp. 64–72, 2025.

[16] K. M. Hosny, M. A. Mohammed, R. A. Salama, and A. M. Elshewey, "Explainable ensemble deep learning-based model for brain tumor detection and classification," *Neural Comput. Appl.*, vol. 37, no. 3, pp. 1289–1306, 2025.

[17] S. K. Mathivanan, S. Srinivasan, M. S. Koti, V. S. Kushwah, R. B. Joseph, and M. A. Shah, "A secure hybrid deep learning framework for brain tumor detection and classification," *J. Big Data*, vol. 12, no. 1, p. 72, 2025.

[18] Y. Pande and J. Chaki, "Brain tumor detection across diverse MR images: An automated triple-module approach integrating reduced fused deep features and machine learning," *Results Eng.*, vol. 25, p. 103832, 2025.

[19] A. Abdusalomov *et al.*, "Accessible AI diagnostics and lightweight brain tumor detection on medical edge devices," *Bioengineering*, vol. 12, no. 1, p. 62, 2025.

[20] I. Tuncer *et al.*, "FlexiCombFE: A flexible, combination-based feature engineering framework for brain tumor detection," *Biomed. Signal Process. Control*, vol. 104, p. 107538, 2025.

[21] S. A. Qureshi, T. Sadiq, A. Usman, A. Khawar, S. T. H. Shah, and A. ul Rehman, "SAlexNet: Superimposed AlexNet using residual attention mechanism for accurate and efficient automatic primary brain tumor detection and classification," *Results Eng.*, vol. 25, p. 104025, 2025.

[22] A. Ishaq, F. U. M. Ullah, P. Hamandawana, D.-J. Cho, and T.-S. Chung, "Improved EfficientNet architecture for multi-grade brain tumor detection," *Electronics*, vol. 14, no. 4, p. 710, 2025.

[23] A. K. Sharma *et al.*, "Brain tumor classification using the modified ResNet50 model based on transfer learning," *Biomed. Signal Process. Control*, vol. 86, p. 105299, 2023.

[24] A. Anaya-Isaza, L. Mera-Jiménez, L. Verdugo-Alejo, and L. Sarasti, "Optimizing MRI-based brain tumor classification and detection using AI: A comparative analysis of neural networks, transfer learning, data augmentation, and the cross-transformer network," *Eur. J. Radiol. Open*, vol. 10, p. 100484, 2023.

[25] R. Disci, F. Gurcan, and A. Soylu, "Advanced brain tumor classification in MR images using transfer learning and pre-trained deep CNN models," *Cancers (Basel).*, vol. 17, no. 1, p. 121, 2025.

[26] M. R. Shoaib *et al.*, "Improving brain tumor classification: An approach integrating pre-trained CNN models and machine learning algorithms," *Heliyon*, vol. 11, no. 10, 2025.

[27] R. İncir and F. Bozkurt, "Improving brain tumor classification with combined convolutional neural networks and transfer learning," *Knowledge-Based Syst.*, vol. 299, p. 111981, 2024.

[28] N. Shamshad *et al.*, "Enhancing brain tumor classification by a comprehensive study on transfer learning techniques and model efficiency using MRI datasets," *IEEe Access*, vol. 12, pp. 100407–100418, 2024.

[29] A. Younis *et al.*, "Abnormal brain tumors classification using resnet50 and its comprehensive evaluation," *IEEE Access*, vol. 12, pp. 78843–78853, 2024.

[30] N. Bibi, F. Wahid, Y. Ma, S. Ali, I. A. Abbasi, and A. Alkhayyat, "A transfer learning-based approach for brain tumor classification," *IEEE Access*, vol. 12, pp. 111218–111238, 2024.

[31] S. M. Rasa *et al.*, “Brain tumor classification using fine-tuned transfer learning models on magnetic resonance imaging (MRI) images,” *Digit. Heal.*, vol. 10, p. 20552076241286140, 2024.

[32] A. Amarnath, A. Al Bataineh, and J. A. Hansen, “Transfer-learning approach for enhanced brain tumor classification in MRI imaging,” *BioMedInformatics*, vol. 4, no. 3, pp. 1745–1756, 2024.

[33] K. He, X. Zhang, S. Ren, and J. Sun, “Identity mappings in deep residual networks,” in *European conference on computer vision*, Springer, 2016, pp. 630–645.

[34] Z. Gong *et al.*, “A multi-center, multi-parametric MRI dataset of primary and secondary brain tumors,” *Sci. data*, vol. 11, no. 1, p. 789, 2024.