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Optimization of CNN Architectures for Accurate Brain Tumor Classification: A Comparative Study

Optimalisasi Arsitektur CNN untuk Klasifikasi Tumor Otak yang Akurat: Studi Komparatif

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ABSTRAK

Klasifikasi tumor otak secara otomatis dari citra MRI menjadi penting dalam mendukung diagnosis dini dan perencanaan pengobatan yang lebih efektif. Namun, proses diagnosis secara manual masih menghadapi kendala seperti subjektivitas dan keterbatasan sumber daya medis. Penelitian ini bertujuan untuk mengoptimalkan klasifikasi tumor otak melalui analisis komparatif terhadap enam arsitektur *Convolutional Neural Network (CNN)*, yaitu VGG16, *VGG19*, *MobileNet*, *InceptionV3*, *AlexNet*, dan *Xception*. Dataset citra MRI diperoleh dari repositori terbuka, kemudian diproses melalui tahap normalisasi, reduksi noise, segmentasi, dan augmentasi data. Seluruh arsitektur CNN diimplementasikan menggunakan transfer learning, dan pelatihan dilakukan dengan parameter yang seragam. Evaluasi performa dilakukan berdasarkan metrik akurasi, sensitivitas, spesifisitas, dan F1-score. Hasil penelitian menunjukkan bahwa arsitektur *Xception* dan *InceptionV3* memberikan performa klasifikasi terbaik dengan akurasi validasi masing-masing sebesar 97,9% dan 96,1%. *MobileNet* juga menunjukkan hasil kompetitif sebesar 95,6%, dengan keunggulan efisiensi komputasi. Sebaliknya, VGG19 dan *AlexNet* mencatatkan akurasi validasi yang lebih rendah dan menunjukkan indikasi *overfitting*. Temuan ini menegaskan bahwa arsitektur modern dengan *depthwise separable convolution* dan residual connection lebih efektif dalam mengekstraksi fitur kompleks dari citra MRI otak. Dengan demikian, arsitektur seperti *Xception* dan *MobileNet* menjadi kandidat kuat untuk diimplementasikan dalam sistem diagnosis berbantuan komputer di lingkungan klinis dengan keterbatasan sumber daya.

Kata Kunci: Classification; Deep Learning; Image Processing; Identification; Medical Science

ABSTRACT

Automatic classification of brain tumors from MRI images is crucial for supporting early diagnosis and improving treatment planning. However, manual diagnostic processes remain limited by subjectivity and resource constraints. This study aims to optimize brain tumor classification by conducting a comparative analysis of six Convolutional Neural Network (CNN) architectures: VGG16, VGG19, MobileNet, InceptionV3, AlexNet, and Xception. The MRI datasets were sourced from open repositories and processed through normalization, noise reduction, segmentation, and data augmentation. All CNN models were implemented using transfer learning and trained under consistent parameters. Model performance was evaluated based on accuracy, sensitivity, specificity, and F1-score. The results revealed that the Xception and InceptionV3

architectures achieved the highest classification performance, with validation accuracies of 97.9% and 96.1%, respectively. MobileNet also performed competitively at 95.6%, offering notable computational efficiency. In contrast, VGG19 and AlexNet yielded lower validation accuracies and exhibited signs of overfitting. These findings highlight the effectiveness of modern CNN architectures that incorporate depthwise separable convolutions and residual connections in extracting complex features from brain MRI images. Therefore, models such as Xception and MobileNet are strong candidates for implementation in computer-aided diagnosis systems in resource-constrained clinical environments.

Keywords: *Classification; Deep Learning; Image Processing; Identification; Medical Science*

1. INTRODUCTION

The rapid advancement of artificial intelligence (AI) in medical imaging has significantly transformed diagnostic processes, particularly in the field of neuro-oncology (Niño, Bernardino, and Domingues 2024). Among various life-threatening diseases, brain tumors remain one of the most challenging conditions to diagnose and manage due to their heterogeneous characteristics and complex manifestation within cranial structures (Ardalan and Subbian 2022).

Early and accurate classification of brain tumors is critical, as it directly influences treatment decisions and prognostic outcomes (Benabid et al. 2024). Conventional diagnostic methods such as biopsy and manual interpretation of Magnetic Resonance Imaging (MRI) are often limited by subjectivity, time constraints, and the availability of expert radiologists (Sowjanya, Reddy, and Raveena 2023).

To address these challenges, computer-aided diagnosis (CAD) systems leveraging deep learning techniques have emerged as a promising solution (Abdelaziz Ismael, Mohammed, and Hefny 2020; Kaba et al. 2023). Convolutional Neural Networks (CNNs), in particular, have demonstrated remarkable efficacy in various image classification tasks and have shown substantial potential in medical applications, including brain tumor identification from MRI scans.

Several CNN architectures—such as AlexNet, VGGNet, GoogLeNet, ResNet (Buchade and Kantipudi 2024; Jain et al. 2023; Shedbalkar and Prabhushetty 2024; Srinivasan et al. 2024), and DenseNet—have been successfully employed in tumor classification studies with varying degrees of accuracy and computational efficiency (Alshuhail et al. 2024; Kesav and Rajini 2024). However, despite their promising results, a comprehensive and comparative analysis of these architectures tailored specifically to brain tumor classification remains underexplored, particularly within the context of diverse MRI datasets.

The primary limitation in current methodologies lies in the lack of consensus regarding the optimal CNN architecture that balances classification accuracy, model complexity, and practical deploy ability in clinical environments (Malik et al. 2024; Shewale and Daruwala 2023). Some models, like VGGNet, offer high classification performance but at the cost of extensive computational resources (N.Huda, S.Y. Prayogi, M.A. Ahmad 2022; Shedbalkar and Prabhushetty 2024; Venkatesh et al. 2020).

Others, like MobileNetV3, provide lightweight alternatives with acceptable accuracy but require further validation against more complex tumors (Mathivanan et al. 2024; Yebasse, Cheoi, and Ko 2023). Moreover, many existing studies do not systematically compare model performance using uniform preprocessing techniques or consistent evaluation metrics, thereby limiting the reproducibility and generalizability of their findings.

Given this background, the present study addresses the following key research questions:

1. How do different CNN architectures perform in classifying brain tumors using MRI images?
2. Can transfer learning enhance classification accuracy, particularly in distinguishing malignant from benign tumors?
3. Which architecture offers the best trade-off between accuracy, computational efficiency, and applicability in clinical diagnostics?

To answer these questions, we propose a comparative study that evaluates the performance of various CNN models, including AlexNet, VGG16, GoogLeNet, ResNet, and InceptionV3, using a standardized dataset and uniform preprocessing pipeline (Ali et al. 2022; Ghosh et al. 2024; Jain et al. 2023). The models are assessed using key performance metrics such as accuracy, sensitivity, specificity, and F1-score (Potadar, Holambe, and Chile 2024).

The significance of this study lies in its potential to inform the selection of CNN

architectures for practical implementation in computer-aided brain tumor diagnosis systems, particularly in resource-constrained healthcare settings (Bintang, Novirianthy, and Hidayaturrahmi 2024; Irianto, Karnila, and Yuliawati 2024; Kumaar et al. 2024). By identifying the most accurate and computationally feasible model, this research contributes to improving early detection efforts and supporting timely clinical interventions.

The remainder of this paper is structured as follows: Section 2 presents the related work and highlights the theoretical and practical gaps addressed by this study. Section 3 details the methodology, including dataset preprocessing, model implementation, and evaluation strategies. Section 4 discusses the experimental results and comparative performance analysis. Section 5 offers concluding remarks and outlines future research directions.

2. RELATED WORK

The application of deep learning techniques, particularly Convolutional Neural Networks (CNNs), has seen a marked rise in the field of brain tumor classification using medical imaging modalities such as Magnetic Resonance Imaging (MRI) (Oksuz et al. 2020; Oladimeji and Ibitoye 2023; Shreeharsha 2024). Numerous studies have reported promising results employing various CNN architectures, yet inconsistencies in methodological design and a lack of comparative evaluations remain prevalent.

One of the earliest architectures adopted in brain tumor classification is AlexNet, which demonstrated the foundational potential of CNNs in image classification tasks. (Sarkar et al. 2023) combined AlexNet with machine learning classifiers and observed moderate classification accuracy for MRI-based tumor images, though the model struggled to capture high-level abstractions due to its relatively shallow architecture (Huda and Ku-Mahamud 2025; Huda and Safitri 2024).

VGGNet, particularly the VGG16 and VGG19 variants, has been extensively employed owing to its simple and uniform architecture of stacked 3×3 convolutional layers. Studies by (Agarwal et al. 2023) and (Babu Vimala et al. 2023) report that VGGNet consistently achieves high accuracy in classifying gliomas, meningiomas, and pituitary tumors. However, its major drawback lies in the excessive number of parameters, leading to high memory consumption and reduced suitability for real-time clinical deployment.

The GoogLeNet architecture, based on Inception modules, was introduced to enhance computational efficiency by capturing multi-scale features within the same layer. It has shown competitive performance in tumor classification tasks, with (Malakouti, Bagher Menhaj, and Abolfazl Suratgar 2024) demonstrating its ability to achieve an accuracy rate exceeding 99% on benchmark datasets. Nonetheless, its complex structure demands careful tuning, especially when applied to heterogeneous medical datasets.

ResNet, which introduced residual learning through shortcut connections, has been recognized for enabling deeper network training without degradation. Several studies, including those by (Raza et al. 2024) and (Musa et al. 2024), have leveraged ResNet variants (e.g., ResNet-50, ResNet-101) for brain tumor classification, achieving high levels of accuracy and robustness. However, overfitting remains a concern, particularly in scenarios involving limited training samples.

DenseNet offers an alternative approach by introducing dense connections between layers, ensuring maximum information flow and mitigating the vanishing gradient problem. It has recently gained traction in brain tumor research, with Alshammari (2023) proposing a DenseNet-Hybrid architecture that outperformed traditional CNNs by enhancing feature reuse and reducing model redundancy.

Transfer learning has also emerged as a viable strategy to improve classification performance, especially when dealing with small or imbalanced datasets. (Amin et al. 2022) and (Hastomo et al. 2024) illustrated the effectiveness of fine-tuning pretrained CNN models, such as MobileNetV3 and InceptionResNetV2, for improved detection of malignant tumors, underscoring the utility of transfer learning in medical contexts with limited annotated data.

Despite these advances, most existing studies evaluate CNN architectures in isolation, often utilizing different datasets, preprocessing pipelines, or evaluation metrics, which hinders cross-comparability. Furthermore, little emphasis has been placed on balancing model accuracy with computational feasibility, a key consideration for deployment in clinical settings—particularly in resource-constrained environments like many hospitals in Indonesia.

In light of these gaps, this study aims to provide a systematic and comparative evaluation of multiple CNN architectures using a uniform dataset and standardized performance metrics. By doing so, it seeks to offer actionable insights

into selecting the most suitable CNN model for practical application in brain tumor diagnosis.

3. METHODOLOGY

This study employs a systematic and comparative approach to evaluate the performance of several Convolutional Neural Network (CNN) architectures in classifying brain tumors from Magnetic Resonance Imaging (MRI) data. The methodology encompasses dataset preparation, preprocessing, model implementation, training and validation, performance evaluation, and comparative analysis.

3.1 Dataset Collection

The research utilizes publicly available MRI brain tumor datasets compiled from multiple open-access sources (**Figure 1**), including:

1. Kaggle Brain MRI Dataset
2. National Institutes of Health (NIH) Medical Imaging Databases
3. UC Irvine Machine Learning Repository (UCI-MLR)
4. Public Health Image Library (PHIL)

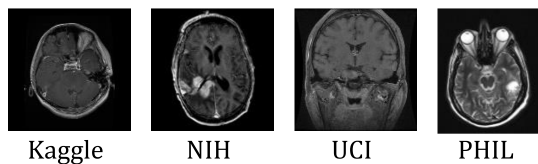


Figure 1. Dataset Multiple

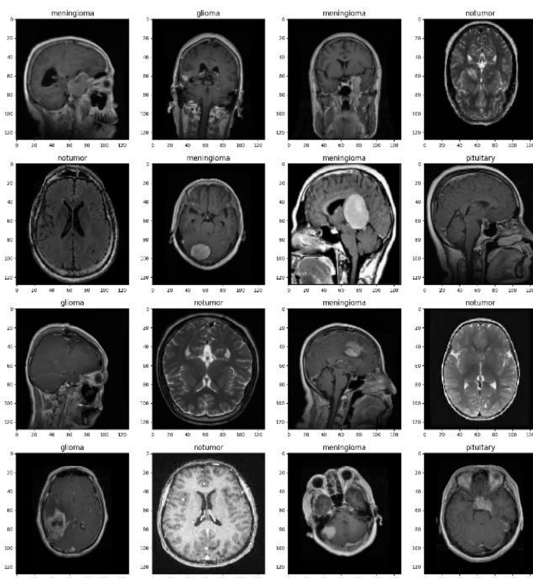


Figure 2. Dataset Sample

These datasets (**Figure 2**) include T1-weighted and contrast-enhanced T1 MRI images, annotated with three primary tumor classes: glioma, meningioma, and pituitary tumor, along with non-tumorous (normal) brain images. Data was curated to ensure adequate representation across all classes, with care taken to anonymize and pre-validate the images for quality.

3.2 Image Processing

To ensure uniformity and enhance model performance, the MRI images underwent several preprocessing steps:

1. Normalization
   Pixel intensity values were normalized to the range [0, 1] to standardize the data distribution and expedite convergence during training.
2. Noise Removal
   Gaussian blur and median filtering techniques were applied to reduce image noise, preserving relevant anatomical structures critical for tumor identification (**Figure 4**).
3. Tumor Segmentation
   Semi-automatic thresholding and morphological operations were employed to isolate tumor regions from healthy brain tissues, allowing the models to focus on salient features.
4. Data Augmentation
   To address class imbalance and prevent overfitting, augmentation techniques such as rotation, horizontal and vertical flipping, zooming, and random cropping were applied, increasing the dataset's variability and generalization capability (**Figure 3**).

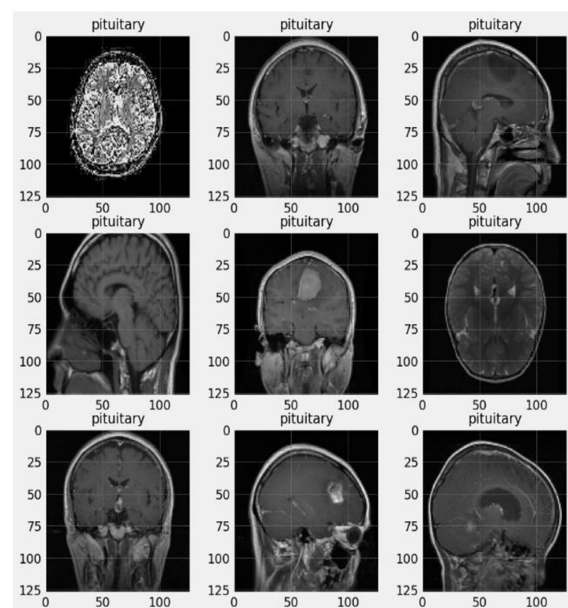


Figure 3. Image Preprocessing (Augmentation)

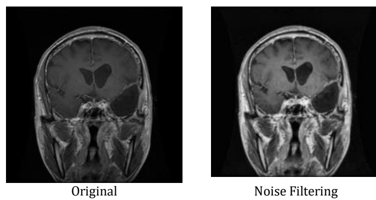


Figure 4. Image Preprocessing (Noise Filtering)

3.3 Experimental Setup and Model Architectures

The experimental phase involved the implementation and evaluation of six prominent CNN architectures:

1. AlexNet
2. VGG16
3. GoogLeNet (Inception V1)
4. InceptionV3
5. ResNet50
6. DenseNet121

Each model was trained using the same dataset split and preprocessing pipeline to ensure comparability. The models were implemented using Python with TensorFlow and Keras libraries, trained on NVIDIA GPU hardware to accelerate computational efficiency.

3.4 Training and Validation Strategy

The dataset was divided into training (70%) and testing (30%) sets, with a 10-fold cross-validation applied during training to minimize variance and improve reliability. Transfer learning was employed by initializing models with pretrained weights on the ImageNet dataset, followed by fine-tuning of higher convolutional layers to adapt to domain-specific features in brain MRI images.

Hyperparameters were selected based on preliminary grid search experiments:

1. Learning rate: 1e-4
2. Batch size: 32
3. Optimizer: Adam
4. Epochs: 50 (with early stopping based on validation loss)

3.5 Performance Metrics

Model performance was evaluated using a comprehensive set of metrics commonly used in medical image classification (Gayathri and Kumar 2024):

1. Accuracy (ACC)
2. Precision (P)
3. Recall (R) / Sensitivity
4. F1-Score (F1)
5. Specificity (SPC)

These metrics were calculated for each class, and the mean values were used to assess overall model performance. A confusion matrix was also constructed to visualize classification results and identify common misclassifications.

3.6 Comparative Analysis

Following individual model evaluations, a comparative analysis was conducted to rank architectures based on their diagnostic performance, computational cost, and memory footprint. This analysis aids in identifying architectures that offer an optimal trade-off between accuracy and efficiency—critical for integration in real-world clinical settings, particularly in low-resource environments.

4. RESULTS AND DISCUSSIONS

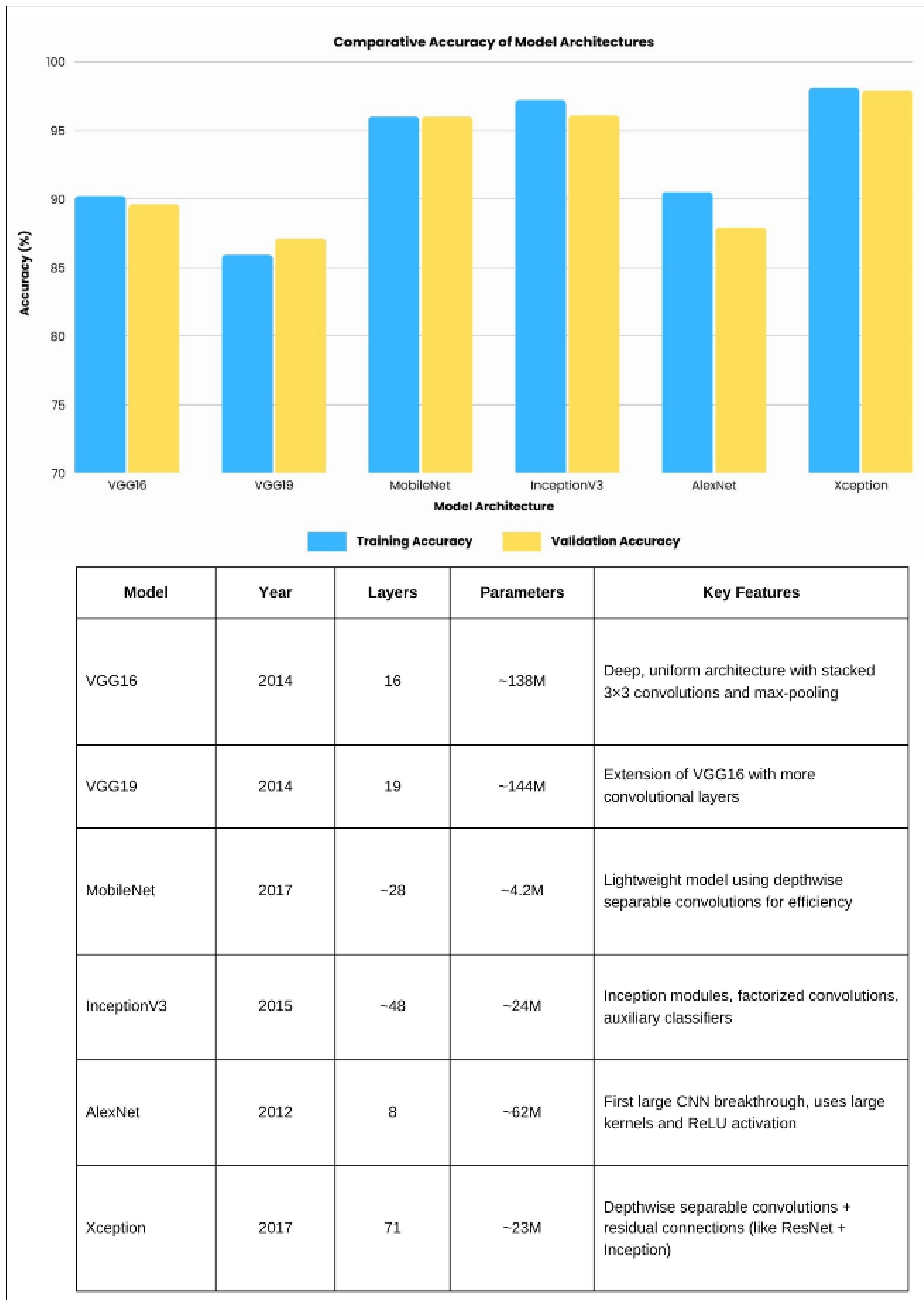
This section presents the performance evaluation of six Convolutional Neural Network (CNN) architectures—VGG16, VGG19, MobileNet, InceptionV3, AlexNet, and Xception—on the brain tumor classification task. The results are analyzed based on both training and validation accuracy, as depicted in Table 1.

4.1. Model Accuracy Analysis

Figure 5 illustrates the comparative accuracy of each model architecture. The Xception architecture yielded the highest classification performance, achieving 98.1% training accuracy and 97.9% validation accuracy, followed closely by InceptionV3 with 97.2% training accuracy and 96.1% validation accuracy. These results suggest that deeper and more optimized models with residual and separable convolution layers (as seen in Xception and Inception architectures) are better suited for capturing the complex features of brain MRI data.

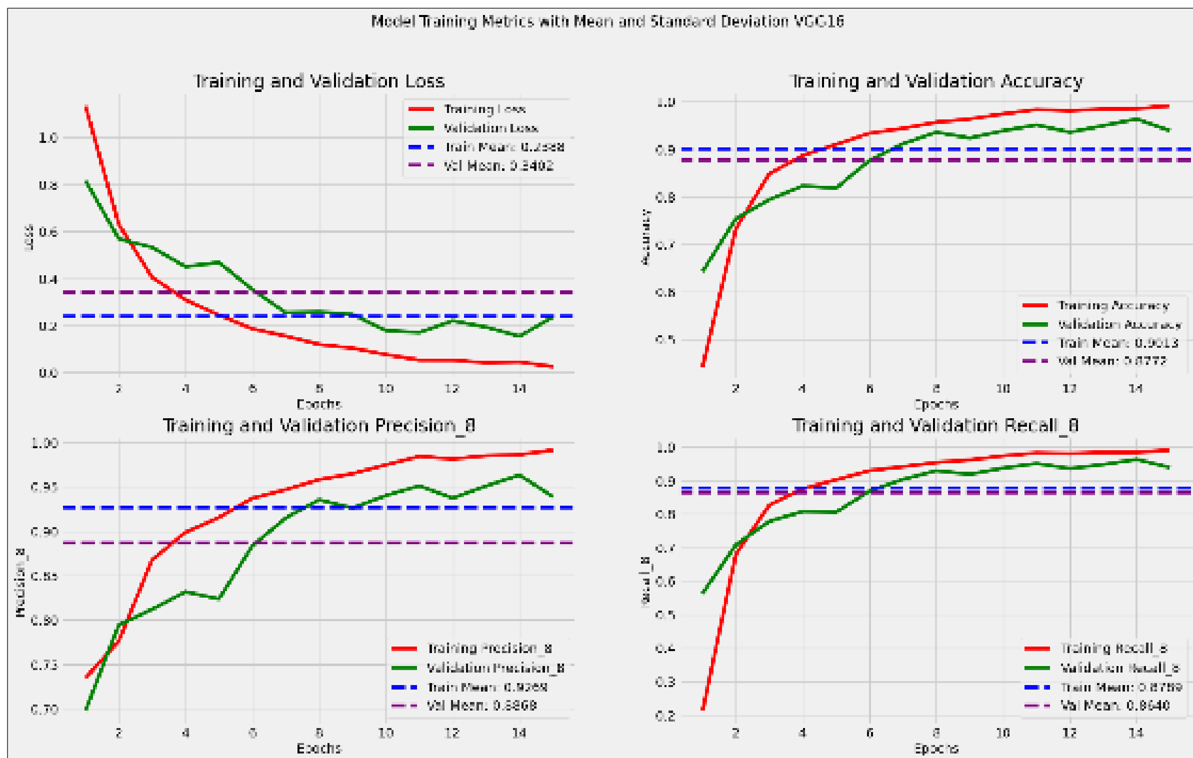
In contrast, VGG19 and AlexNet demonstrated relatively lower validation accuracies of 87.1% and 87.9%, respectively. While their training accuracies were moderately high (85.9% and 90.5%), the larger gap between training and validation accuracy indicates potential overfitting, suggesting that these architectures may not generalize well to unseen data.

MobileNet, a lightweight architecture designed for resource-constrained environments, performed competitively with 96.0% accuracy for both training and validation. This highlights its strong generalization capability despite its relatively shallow depth and reduced parameter count, making it an attractive candidate for deployment on mobile or edge devices.

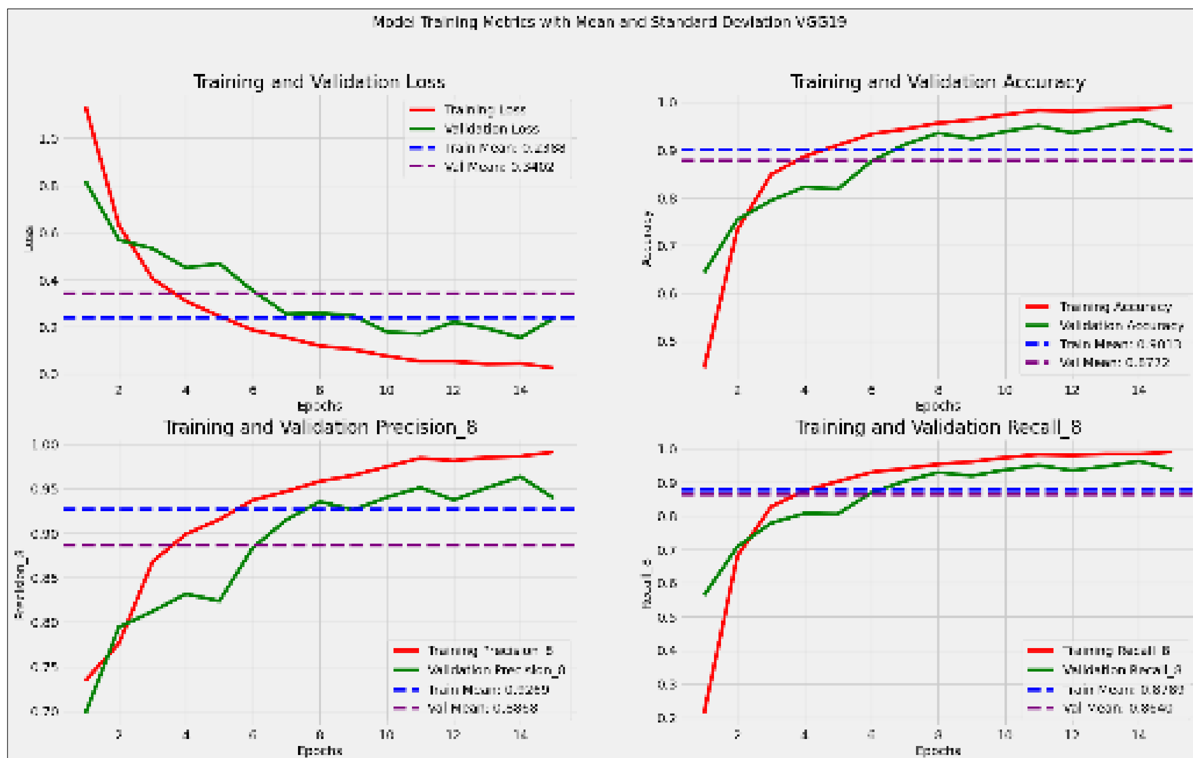


Model	Year	Layers	Parameters	Key Features
VGG16	2014	16	~138M	Deep, uniform architecture with stacked 3×3 convolutions and max-pooling
VGG19	2014	19	~144M	Extension of VGG16 with more convolutional layers
MobileNet	2017	~28	~4.2M	Lightweight model using depthwise separable convolutions for efficiency
InceptionV3	2015	~48	~24M	Inception modules, factorized convolutions, auxiliary classifiers
AlexNet	2012	8	~62M	First large CNN breakthrough, uses large kernels and ReLU activation
Xception	2017	71	~23M	Depthwise separable convolutions + residual connections (like ResNet + Inception)

Figure 5. Experiment Results



(a)



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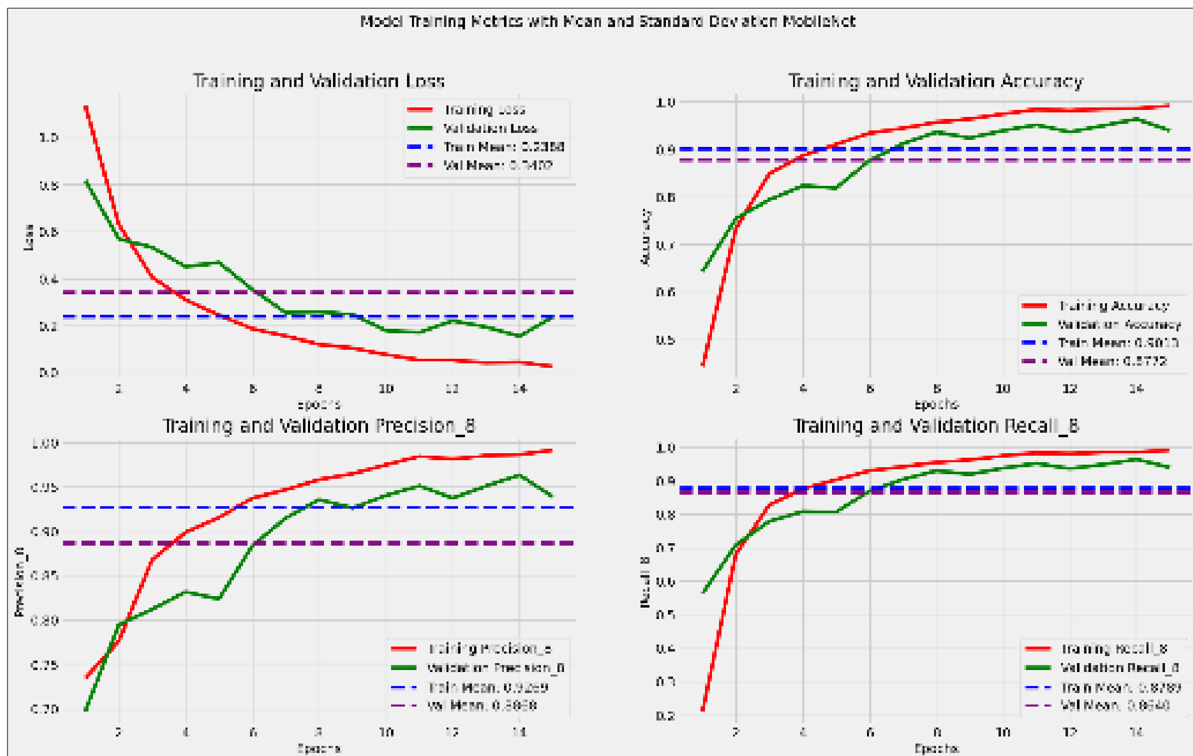

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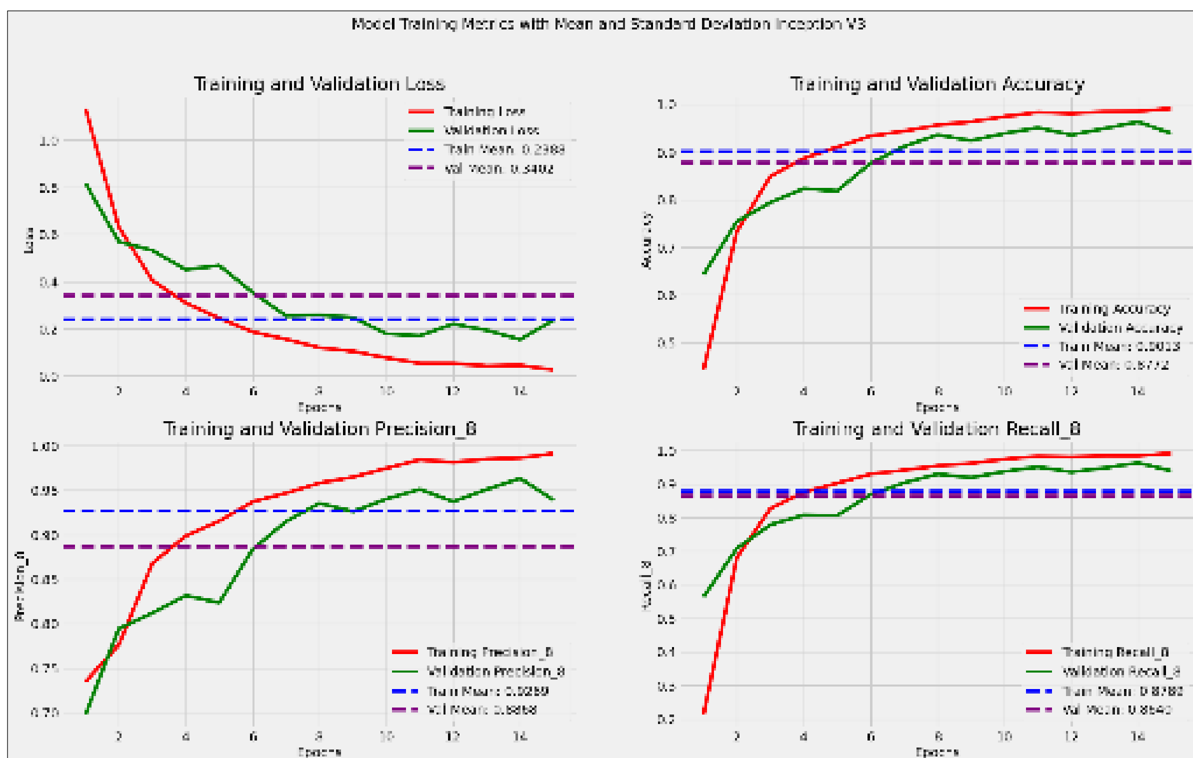

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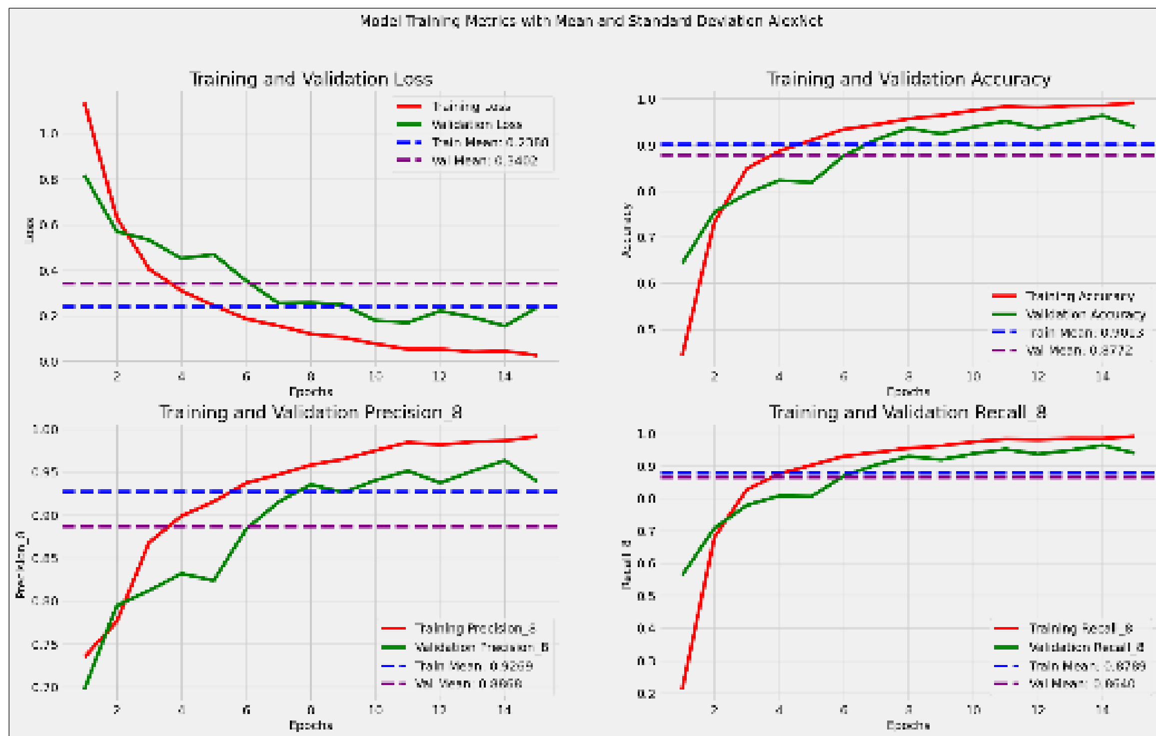

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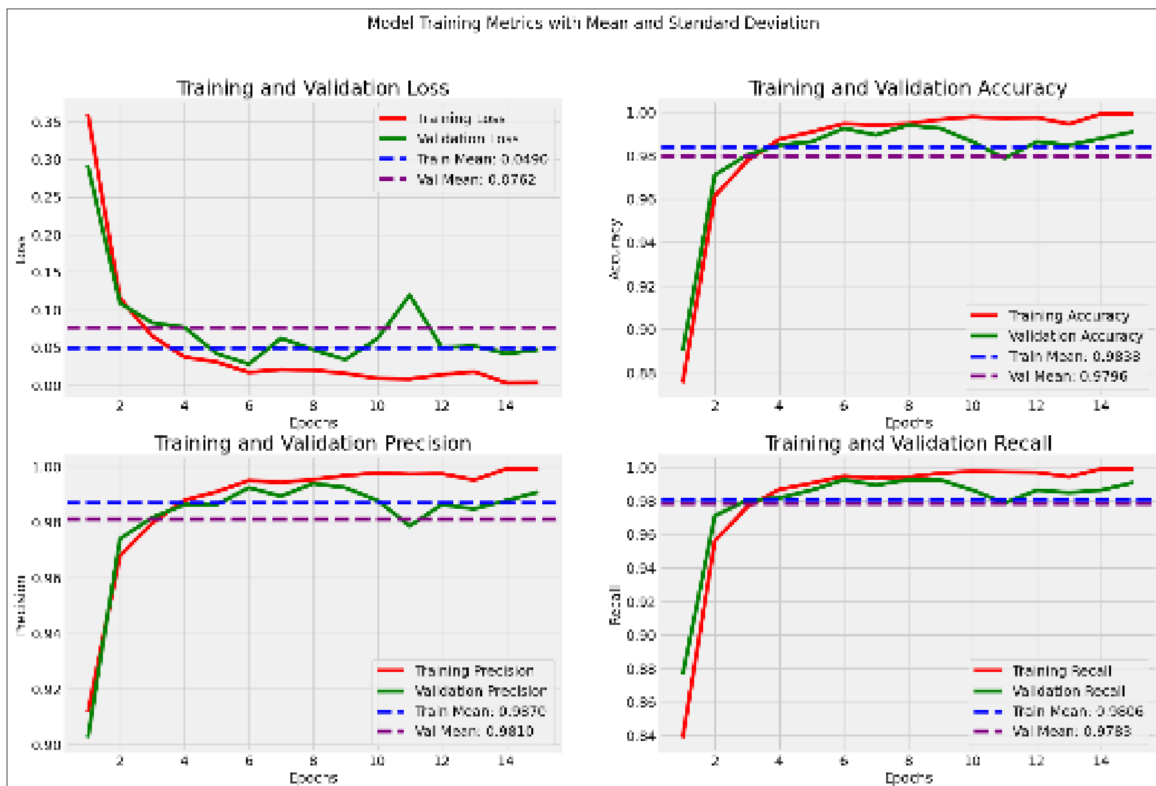

(f)

Figure 6. Experiment Results Graph VGG16(a), VGG19(b), MobileNet (c), InceptionV3(d), AlexNet(e), Xception (f)

4.2. Discussion and Comparative Evaluation

The results (**Figure 6**) demonstrate that model depth and architectural innovation significantly influence classification performance. The Xception model, which combines depthwise separable convolutions and

residual connections, showed exceptional performance and minimal overfitting. Its superior accuracy suggests that such architectural enhancements are effective in extracting discriminative features from brain tumor MRI images.

InceptionV3 also performed well, corroborating the efficacy of inception modules in handling multi-scale image features. MobileNet's balance between performance and computational efficiency is noteworthy, indicating its suitability for real-time clinical applications in low-resource settings. The relatively poorer performance of VGG-based models may be attributed to their uniform and deep convolutional layers without architectural modularity or residual connections, which limits their capacity to generalize complex image patterns.

Additionally, AlexNet's performance, while historically significant, appears outdated compared to more recent architectures, reaffirming the importance of continued innovation in CNN design.

4.3. Implications for Clinical Integration

The empirical evidence suggests that CNN architectures such as Xception and MobileNet hold substantial promise for automated brain tumor diagnosis. Their ability to accurately classify tumor types from MRI data, when paired with minimal overfitting, indicates potential for integration into clinical decision-support systems (CDSS). Moreover, MobileNet's efficiency makes it a viable candidate for deployment on portable diagnostic tools, aiding rapid and accessible diagnoses in underserved regions.

5. CONSLUSIONS

This study has conducted a comparative analysis of six prominent Convolutional Neural Network (CNN) architectures—VGG16, VGG19, MobileNet, InceptionV3, AlexNet, and Xception—for the task of brain tumor classification using MRI imaging data. The evaluation focused on training and validation accuracy as the primary performance indicators.

The experimental findings demonstrate that the Xception architecture achieved the highest classification performance, with 98.1% training accuracy and 97.9% validation accuracy, followed by InceptionV3 and MobileNet, which also exhibited strong generalization capabilities. In contrast, VGG19 and AlexNet presented relatively lower performance, with notable gaps between training and validation accuracies, indicating potential overfitting.

From a methodological standpoint, architectures that incorporate depthwise separable convolutions, inception modules, and residual connections are more effective in capturing the complex visual features of brain MRI images. Furthermore, MobileNet's efficient performance highlights the feasibility of using lightweight models for clinical applications in environments with limited computational resources.

In conclusion, this study underscores the importance of selecting an optimal CNN architecture tailored to the characteristics of medical imaging data. The results support the potential implementation of advanced CNN models such as Xception and MobileNet in computer-aided diagnosis systems for brain tumor detection. Future research may expand this work by incorporating segmentation techniques, multi-class tumor grading, explainable AI approaches, and evaluation across more diverse datasets to further enhance the reliability and interpretability of the models.

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