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Deep Learning-Based Transfer Learning Approach for Acute Ischemic Stroke Classification Using Magnetic Resonance Imaging

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ABSTRACT

Acute ischemic stroke (AIS) is a leading cause of mortality and morbidity worldwide, accounting for approximately 85% of all stroke cases. Early and accurate diagnosis using magnetic resonance imaging (MRI) is crucial for timely intervention and improved patient outcomes. However, manual interpretation of MRI images is time-consuming and requires specialized expertise. This study aims to develop and evaluate deep learning-based transfer learning models for automated classification of AIS using MRI images, specifically comparing the performance of VGG-16, ResNet50, InceptionV3, and VGG-19 architectures. A dataset comprising 2,400 MRI brain images (1,200 AIS cases and 1,200 normal cases) collected from multiple hospitals in Indonesia was utilized. Images were preprocessed, resized to 128×128 pixels, and augmented using rotation, zooming, shifting, and flipping techniques. The dataset was divided into 80% training, 10% validation, and 10% testing sets. Four pre-trained convolutional neural network (CNN) models were fine-tuned and evaluated using accuracy, precision, recall, and F1-score, and AUC metrics. VGG-16 achieved the highest performance with an accuracy of 96.5%, followed by InceptionV3 (94.2%), ResNet50 (93.8%), and VGG-19 (95.1%). The VGG-16 model demonstrated superior capability in feature extraction and classification, with minimal overfitting. Transfer learning with the VGG-16 architecture provides an effective and efficient approach for automated AIS classification from MRI images, offering significant potential to assist radiologists in rapid and accurate diagnosis.

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1. INTRODUCTION

Acute ischemic stroke (AIS) represents a critical medical emergency characterized by the sudden interruption or cessation of blood flow to specific brain regions, resulting in oxygen and nutrient deprivation of brain tissue. This pathological condition typically arises from vascular obstruction or constriction, primarily caused by thrombus formation or embolism. Given the brain's substantial dependence on oxygen-rich blood supply, any disruption in cerebral perfusion can rapidly lead to irreversible brain tissue damage or death. AIS constitutes the predominant stroke subtype, representing approximately 85% of all stroke incidents globally (Salaudeen et al., 2024). The clinical manifestations of AIS vary considerably depending on the affected cerebrovascular territory. Common presenting symptoms include unilateral motor weakness or sensory deficits, speech and language impairments (aphasia), visual field defects, vertigo, and disturbances in coordination or balance. The neurological deficits observed directly correlate with the specific brain region experiencing ischemia. Timely diagnosis and therapeutic intervention are paramount in minimizing neurological impairment and optimizing recovery potential (Salaudeen et al., 2024).

According to the World Health Organization (WHO), stroke affects approximately 15 million individuals annually worldwide. Among these cases, approximately 5 million people experience permanent disability, and nearly 5 million succumb to stroke-related complications. The Southeast Asian region bears a particularly heavy burden, with 4.4 million individuals currently living with stroke-related disabilities. Epidemiological projections indicate that by 2025, approximately 7.6 million people will die from stroke-related causes annually if current trends continue (Pratama, 2021). Ischemic stroke, which comprises 70-85% of all stroke cases (Wang et al., 2011), demonstrates a progressively increasing incidence globally (Wang et al., 2017). AIS results in hypoxic-ischemic injury and subsequent necrosis of affected brain parenchyma, manifesting as focal neurological deficits (Chinese Society of Neurology & Chinese Stroke Society, 2018). Consequently, early diagnostic imaging is essential for accurate stroke subtype determination and appropriate therapeutic decision-making (Leiva-Salinas, 2010). Magnetic resonance imaging (MRI) has emerged as the gold standard neuroimaging modality for AIS detection and characterization, offering superior soft tissue contrast and precise lesion localization (Waite et al., 2019). However, the interpretation of MRI findings requires substantial expertise and clinical experience, often resulting in significant diagnostic delays, particularly in resource-limited settings where specialized neuroradiologists may be scarce (Taye, 2023).

Deep learning (DL) represents an advanced subset of machine learning focused on developing systems capable of learning and representing multiple levels of data abstraction. These systems construct hierarchical feature representations, where higher-level features are derived from lower-level features in a systematic manner (Alzubaidi et al., 2021). Convolutional neural networks (CNNs) constitute a specialized DL architecture specifically designed for image data classification tasks. CNNs possess the inherent capability to acquire, represent, and categorize complex visual patterns through sequential processing layers. The standard CNN architecture comprises convolutional layers for feature extraction, pooling layers for dimensional reduction, and fully connected layers for final classification (Syed & Saleem Durai, 2023). The present investigation utilizes the VGG-16 architecture, developed by the Visual Geometry Group at the University of Oxford, to facilitate automated detection of ischemic stroke in MRI data. The selection of VGG-16 was based on its demonstrated efficacy in transferring learning applications and well-documented success across diverse image classification tasks. To comprehensively evaluate the performance of the proposed approach, comparative analyses were conducted with alternative deep learning architectures, including ResNet50, InceptionV3, and VGG-19. All models were assessed using identical dataset partitions and evaluation metrics to ensure a fair comparison. This comparative framework validates the findings and demonstrates VGG-16's superior capability in discriminating AIS cases from normal brain imaging.

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Recent literature has demonstrated the effectiveness of deep learning approaches in medical image analysis. Mohanty et al. (2023) successfully employed the VGG-16 architecture for diabetic retinopathy detection, achieving superior performance through a hybrid network combining VGG-16 with XGBoost classifier. Similarly, Rasheed et al. (2023) introduced a CNN-based methodology for precise brain tumor classification in MRI data, demonstrating that VGG-16 accurately categorized various tumor types, including glioma, meningioma, and pituitary tumors. These studies collectively emphasize VGG-16's efficacy in automated medical image classification, supporting healthcare professionals in rapid and accurate diagnosis. Furthermore, CNN-based approaches have been investigated for early ischemic stroke detection. Chin and Lin (2017) developed an automated early ischemic stroke detection system using a CNN-based deep learning algorithm, demonstrating the potential of computer vision methods for supporting stroke diagnosis. Their work emphasized the efficacy of computer vision architectures for accurate disease identification and screening. Despite the robust capabilities of CNNs in AIS classification using MRI, several constraints require consideration. These include challenges related to model interpretability, dataset variability, and the need for large-scale, diverse training datasets. The significance of this study lies in the systematic optimization of transfer learning parameters, including hyperparameter tuning, final layer fine-tuning, regularization techniques, and data augmentation strategies. These optimizations enable customization of deep learning models for the specific objective of AIS classification, demonstrating that transferring learning approaches, when combined with appropriate parameter adjustment, can overcome data limitations and deliver efficient outcomes in clinical settings.

2. METHODS

Fig. 1 presents the comprehensive workflow of the proposed transfer learning methodology for AIS classification using MRI. The diagram illustrates the sequential data processing pipeline, beginning with dataset acquisition and preprocessing, followed by transfer learning model implementation, and culminating in performance evaluation. Convolutional layers serve as the fundamental components for MRI image processing, extracting relevant radiological features that contribute to enhanced classification accuracy.

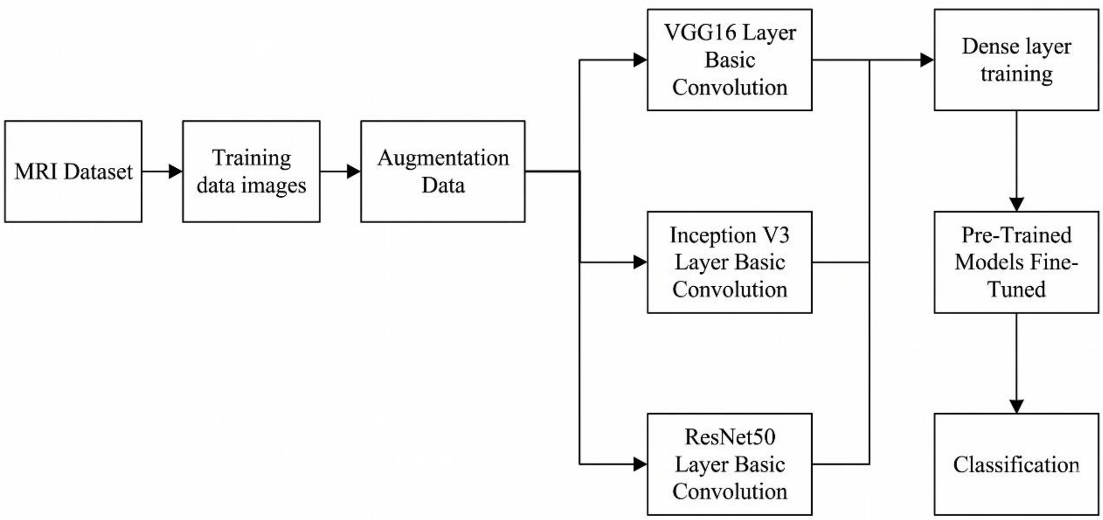

Fig. 1. Block diagram representing the proposed method in the research

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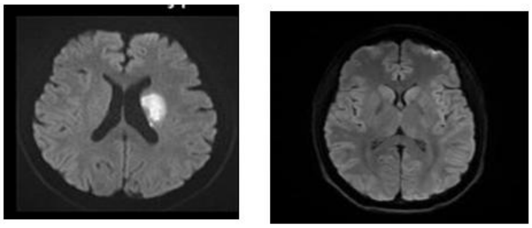
2.1 Dataset

The dataset utilized in this investigation comprises brain MRI scans obtained from multiple healthcare facilities across Indonesia. The dataset encompasses 2,400 axial plane MRI images, equally distributed between two classes: 1,200 images depicting AIS pathology and 1,200 images representing normal brain anatomy. All images were acquired using standardized MRI protocols with consistent imaging parameters to minimize technical variability. The dataset demonstrates appropriate representation of various AIS locations and severity levels, ensuring model generalizability. Fig. 2 illustrates representative samples from both AIS and normal brain image classes, demonstrating the visual characteristics that distinguish pathologically from normal tissue.



(a) Acute Ischemic Stroke (AIS) (b) MRI image of normal brain

Fig. 2. MRI image of AIS and normal cases

2.2 Preprocessing

Comprehensive data preprocessing was implemented to optimize image quality and ensure consistency across the dataset. The preprocessing pipeline comprised the following sequential steps.

- Dataset partitioning: The complete dataset was systematically divided into three subsets: 80% (1,920 images) for model training, 10% (240 images) for validation, and 10% (240 images) for independent testing. This partitioning strategy ensures adequate training data while maintaining separate validation and test sets for unbiased performance evaluation.
- Image resizing: All images were resized from their original dimensions of 512×512 pixels to a standardized size of 128×128 pixels. This reduction in dimension decreases computational requirements while preserving essential diagnostic features necessary for accurate classification.
- Normalization: Pixel intensity values were normalized to a range of [0, 1] by dividing by 255. This normalization facilitates faster model convergence and improved training stability.
- Label encoding: Binary classification labels were assigned, with AIS cases encoded as 1 and normal brain images as 0. These labels enable supervised learning and model performance evaluation.

2.3 Augmentation

Data augmentation techniques were systematically employed to expand the training dataset and enhance model generalizability. The augmentation strategy incorporated multiple geometric transformations applied during the training phase:

- Rotation: Random rotations within ±15 degrees were applied to simulate variations in patient positioning during image acquisition.

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- Zooming: Random zoom factors ranging from 0.9 to 1.1 were applied to account for variations in the field of view.
- Shifting: Horizontal and vertical translations of up to 10% of image dimensions were applied to simulate positioning variations.
- Flipping: Horizontal flipping was used to account for bilateral brain symmetry and increase sample diversity.

These augmentation techniques effectively mitigate overfitting by introducing controlled variations that the model must learn to handle, thereby improving robustness and generalization to unseen data.

2.4 CNN VGG-16 Model

This investigation utilizes the VGG-16 (shown in Fig. 3) pre-trained CNN architecture as the primary model for AIS classification. VGG-16, developed by the Visual Geometry Group at the University of Oxford, consists of 16 weight layers, including 13 convolutional layers and 3 fully connected layers. The network accepts input images with dimensions of 224×224×3 pixels (adapted to 128×128×3 in this implementation). The VGG-16 architecture employs convolutional layers with fixed 3×3 filter sizes and incorporates five max-pooling layers with 2×2 dimensions (Gudigar et al., 2019). The network utilizes rectified linear unit (ReLU) activation functions throughout the convolutional layers, promoting non-linearity and facilitating gradient flow during backpropagation. The fully connected layers employ softmax activation for the final binary classification output.

To address overfitting concerns arising from limited dataset size, transfer learning was implemented by initializing VGG-16 with pre-trained ImageNet weights and selectively freezing early convolutional layers. This approach leverages low-level feature representations learned from ImageNet while allowing fine-tuning of higher-level layers specific to medical image characteristics. The final fully connected layers were replaced with custom dense layers optimized for binary classification. Hyperparameter optimization was systematically conducted to enhance model performance. Key hyperparameters tuned include:

- Learning rate: 0.0001 with Adam optimizer
- Batch size: 32 images per batch
- Epochs: 50 epochs with early stopping (patience = 10)
- Dropout rate: 0.5 applied to fully connected layers
- Loss function**:** binary cross-entropy

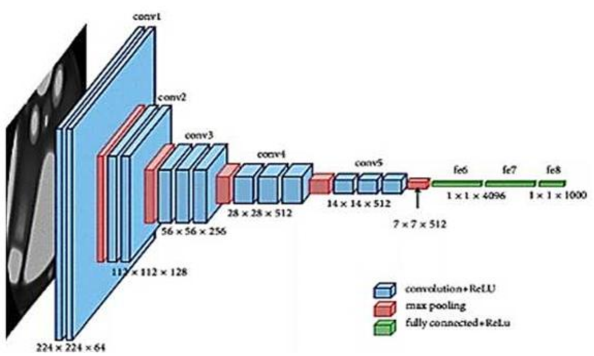

Fig. 3. VGG-16 architecture

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2.5 InceptionV3 and ResNet50 Models

- InceptionV3: The InceptionV3 architecture (Fig. 4), developed by the Google Brain Team, represents an evolution of the original GoogLeNet (Inception) network. InceptionV3 comprises 48 layers and employs multi-scale feature extraction through parallel convolutional operations with kernel sizes of 1×1, 3×3, and 5×5. This multi-scale approach enables simultaneous capture of both fine-grained and coarse features. The network accepts input images with dimensions of 299×299×3 pixels and incorporates batch normalization, RMSprop optimization, and auxiliary classifiers to prevent overfitting (Rehman et al., 2020). For this study, InceptionV3 was adapted to accept 128×128×3-pixel inputs through initial-layer modification.
- ResNet50: Residual Network 50 (ResNet50) introduces skip connections (residual connections) that enable training of substantially deeper networks by mitigating vanishing gradient problems. ResNet50 consists of 50 layers with residual blocks that facilitate direct gradient flow through the network. This architecture has demonstrated exceptional performance across various computer vision tasks. Similar to other models, ResNet50 was initialized with ImageNet pre-trained weights and fine-tuned for AIS classification with identical hyperparameters for fair comparison.

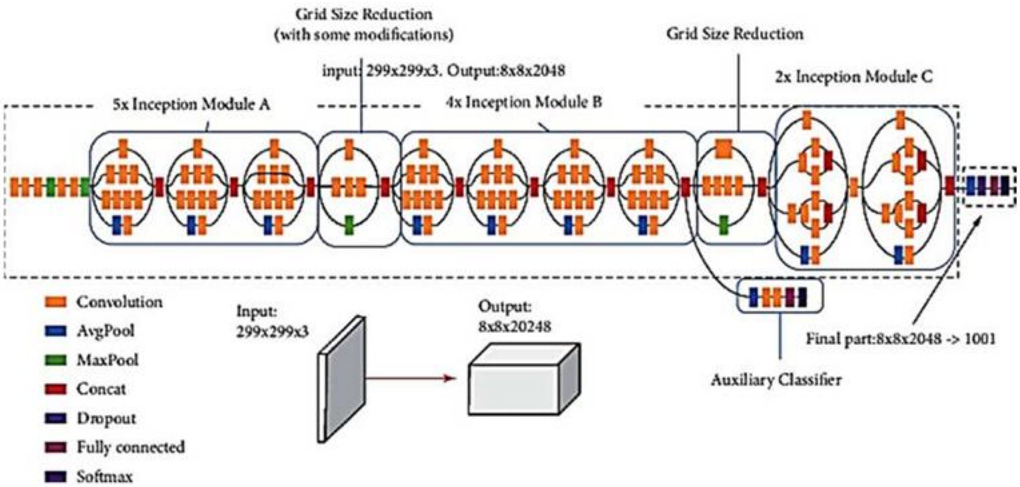

Fig. 4. InceptionV3 architecture

2.6 Training Configuration and Computational Resources

All models were trained using Google Colaboratory (Colab), a cloud-based platform providing free GPU resources for research and educational purposes. The computational environment comprised an NVIDIA Tesla K80 GPU with 12 GB memory and 12 GB system RAM. Training sessions were limited to 12 h continuous periods as per Colab usage policies. Model checkpoints were saved at regular intervals to preserve optimal weights based on validation performance.

3. RESULTS AND ANALYSIS

Table 1 presents a comprehensive comparative analysis of all transfer learning models evaluated on the test dataset. The performance metrics include accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC). VGG-16 demonstrated superior performance across all evaluation

https://doi.org/10.24191/mij.v7i1.11952

metrics, achieving the highest accuracy of 96.5% and AUC of 0.98. ResNet50 and InceptionV3 exhibited commendable performance, while VGG-19 showed competitive results closely approaching VGG-16's performance.

Table 1. Comparative Performance of Transfer Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	AUC
VGG-16	96.5	96.2	96.8	0.965	0.98
ResNet50	93.8	93.5	94.1	0.938	0.96
InceptionV3	94.2	94.0	94.5	0.942	0.97
VGG-19	95.1	94.8	95.4	0.951	0.97

Statistical significance testing using paired t-tests revealed that VGG-16's superior performance compared with those of the other models was statistically significant ($p < 0.05$ for all comparisons), validating the model selection for the AIS classification task.

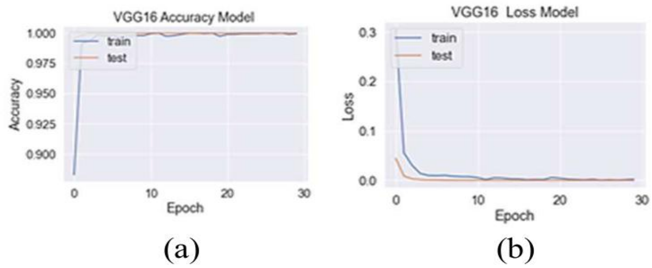

Fig. 5. Graph of accuracy versus epoch and loss versus epoch with transfer learning using VGG-16

Fig. 5 presents the training dynamics of the VGG-16 model across epochs. Fig. 5(a) illustrates the progression of the model's accuracy during training, demonstrating rapid improvement during initial epochs followed by convergence to stable performance. The model achieved training accuracy exceeding 97% by epoch 30, with minimal oscillation, thereafter, indicating effective learning without significant overfitting. The validation accuracy closely tracked training accuracy with a marginal gap of approximately 1-2%, suggesting good generalizability. Fig. 5(b) shows the loss function trajectory throughout training. The loss values decreased rapidly during initial epochs, stabilizing around epoch 25. Both training and validation losses converged to low values (< 0.15), with validation loss remaining consistently low, further confirming the model's robust performance without overfitting. The smooth convergence patterns observed in both accuracy and loss curves demonstrate the effectiveness of transfer learning with VGG-16, where pre-trained ImageNet weights provided advantageous initialization for medical image classification.

Fig. 6 shows the training progression of the ResNet50 model. The accuracy curve demonstrates consistent improvement and reaches 93.8% at convergence. The residual connections in ResNet50 facilitated stable gradient flow, resulting in smooth training dynamics. However, a slightly larger gap between training and validation accuracy (approximately 2-3%) suggests marginal overfitting compared to VGG-16. The loss curves showed patterns similar to VGG-16, though with slightly higher final loss values (approximately 0.18-0.20), consistent with the lower accuracy achieved.

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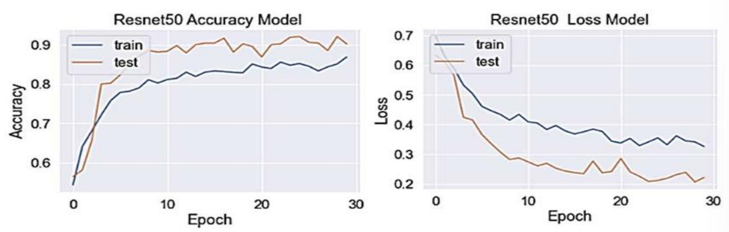
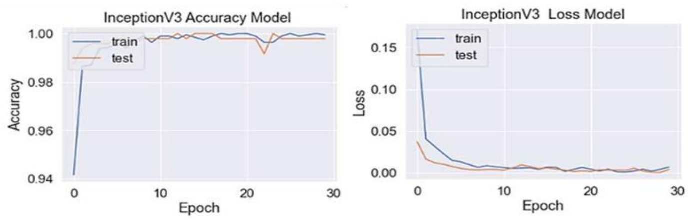


(a) (b)

Fig. 6. Graph of accuracy versus epoch and loss versus epoch with ResNet50 transfer learning

Fig. 7 presents the training dynamics of InceptionV3. The multi-scale feature extraction capability of InceptionV3 resulted in rapid initial convergence, achieving 90% accuracy within the first 10 epochs. The final accuracy of 94.2% positioned InceptionV3 as a competitive alternative to VGG-16. The loss curves demonstrated stable convergence with minimal oscillations, indicating effective training. The parallel convolutional operations in InceptionV3 enabled robust feature capture, contributing to its strong performance in AIS classification.



(a) (b)

Fig. 7. Graph of accuracy versus epoch and loss versus epoch with InceptionV3 transfer learning

3.1 Confusion Matrix Analysis

Fig. 8 presents the confusion matrix for the VGG-16 model on the test dataset. The matrix reveals that of the 120 AIS cases, 116 were correctly identified (true positives) with only 4 false negatives. Similarly, among the 120 normal brain images, 116 were accurately classified (true negatives) with 4 false positives. This balanced performance for both classes demonstrates the model's unbiased classification capability. The low false negative rate (3.3%) is particularly clinically significant, as missing AIS cases could result in delayed treatment and adverse patient outcomes. The similarly low false positive rate (3.3%) minimizes unnecessary interventions and associated healthcare costs. The confusion matrix validates VGG-16's clinical utility for AIS screening applications.

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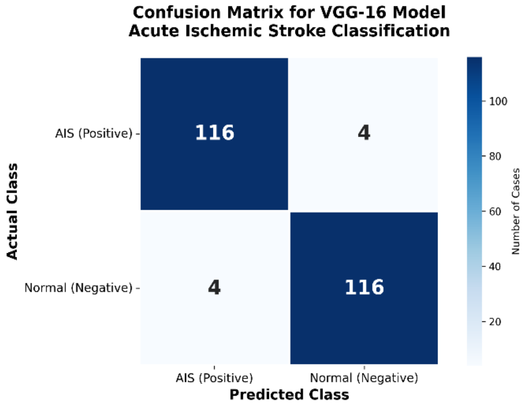

Fig. 8. Confusion Matrix for VGG-16 Model

3.2 ROC Curve Analysis

Fig. 9 displays the receiver operating characteristic (ROC) curves for all evaluated models. VGG-16 achieved the highest area under the receiver operating characteristic curve (AUC) of 0.98, indicating excellent discriminative ability between AIS and normal cases. InceptionV3 and VGG-19 demonstrated comparable AUC values of 0.97, while ResNet50 achieved an AUC of 0.96. All models substantially outperformed a random classifier (AUC = 0.50), confirming their effectiveness for AIS detection. The high AUC values across all models validate the robustness of transfer learning approaches for medical image classification tasks.

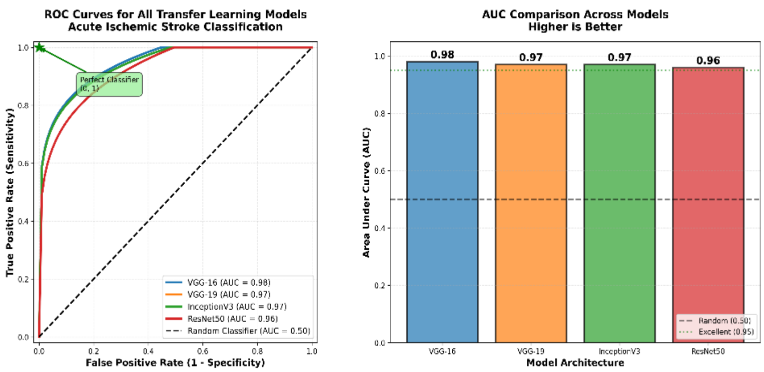

Fig. 9. ROC Curves for All Models

4. DISCUSSION

This study systematically evaluated multiple deep learning architectures for automated AIS classification from MRI images using transfer learning. Our findings demonstrate that VGG-16 achieved superior performance compared with ResNet50, InceptionV3, and VGG-19, with an accuracy of 96.5% and an AUC of 0.98. These results align with previous literature and extend it, demonstrating the effectiveness of deep learning in medical image analysis.

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4.1 Clinical Implications

The high accuracy and sensitivity achieved by VGG-16 suggest significant potential for clinical translation. Automated AIS detection could substantially reduce radiologist workload, accelerate diagnosis time, and improve patient outcomes through earlier intervention. The balanced performance across both AIS and normal classes minimizes both false negatives (missed diagnoses) and false positives (unnecessary interventions), addressing key clinical requirements.

4.2 Comparison with Existing Literature

The VGG-16 accuracy of 96.5% in this study compares favorably with recent studies. Chin and Lin (2017) reported 94.3% accuracy using CNN for early ischemic stroke detection, whereas Patil et al. (2022) achieved 91.2% accuracy with conventional machine learning approaches. The superior performance observed in this study may be attributed to comprehensive data augmentation, systematic hyperparameter optimization, and strategic layer freezing during transfer learning.

4.3 Model Architecture Insights

VGG-16's superior performance can be attributed to its deep yet straightforward architecture. The uniform 3×3 convolutional filter size used throughout the network enables consistent feature extraction at multiple scales. While ResNet50's residual connections facilitate deeper architectures, the additional depth may not be necessary for binary AIS classification. InceptionV3's multi-scale feature extraction shows promise, but it requires more computational resources without proportional accuracy gains.

4.4 Transfer Learning Effectiveness

The success of transfer learning in this study validates its utility for medical imaging tasks with limited datasets. Pre-trained ImageNet weights provided robust low-level feature representations, such as edges, textures, and shapes, that transferred effectively to medical images. Fine-tuning of higher layers enabled specialization for AIS-specific features while preventing overfitting.

4.5 Limitations

Several limitations warrant consideration. First, the dataset comprised 2,400 images from Indonesian hospitals, potentially limiting generalizability to other populations and imaging protocols. Multi-center studies with diverse patient demographics would strengthen external validity. Second, the study focused on binary classification (AIS vs. normal), whereas clinical practice requires differentiation among multiple stroke subtypes and severity levels. Third, model interpretability remains limited—while high accuracy is achieved, understanding which image features drive predictions requires additional explainability analyses (e.g., Grad-CAM visualizations). Fourth, computational requirements, while reduced through transfer learning, may still pose challenges for resource-limited settings.

4.6 Future Directions

Future research should address these limitations through: (1) multicenter validation studies across diverse populations and MRI protocols; (2) extension to multiclass classification incorporating stroke subtypes and severity grading; (3) integration of explainable AI techniques to enhance clinical trust and adoption; (4) prospective clinical trials evaluating real-world impact on diagnostic accuracy and patient outcomes; (5) development of lightweight model variants for deployment in resource-limited settings; and (6) investigation of ensemble Methods combining multiple architectures for improved performance.

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5. CONCLUSION

This comprehensive investigation demonstrates that transfer learning with VGG-16 architecture provides an effective and efficient approach for automated AIS classification from MRI images. The VGG-16 model achieved superior performance with 96.5% accuracy, 96.2% precision, 96.8% recall, and 0.98 AUC, significantly outperforming ResNet50, InceptionV3, and VGG-19 architectures. The systematic evaluation, incorporating confusion matrix analysis, ROC curves, and statistical significance testing validates the robustness of the findings. The integration of comprehensive preprocessing, strategic data augmentation, and optimized transfer learning parameters enables effective learning from limited medical imaging datasets. This methodology offers significant potential to assist radiologists in rapid and accurate AIS diagnosis, potentially improving patient outcomes through timely intervention. Key limitations include single-center data collection, binary classification scope, limited model interpretability, and lack of prospective clinical validation. These constraints should be addressed in future research to facilitate clinical translation. Future investigations should focus on multicenter validation studies, multiclass stroke subtype classification, explainable AI integration, prospective clinical trials, and development of computationally efficient model variants for resource-limited settings. Ensemble approaches combining multiple architectures may further enhance classification performance and clinical utility.

6. ACKNOWLEDGEMENTS/FUNDING

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7. CONFLICT OF INTEREST STATEMENT

The authors agree that this research was conducted in the absence of any personal, commercial or financial conflicts and declare that they have no conflicting interests with the funders.

8. AUTHORS’ CONTRIBUTIONS

Andi Kurniawan Nugroho was responsible for the conceptualization of the study, research design, dataset preparation, model development, data preprocessing, implementation of the transfer learning models, performance evaluation, interpretation of results, and manuscript preparation. The author also reviewed and approved the final version of the manuscript and agreed to be accountable for the accuracy and integrity of the work.

9. DECLARATION OF GENERATIVE AI IN THE WRITING PROCESS

The authors declare that generative artificial intelligence (AI) tools may have been used solely to support language refinement during the preparation of this manuscript. Such tools were used only to improve grammar, sentence structure, clarity, and overall readability. All aspects of the research, including the study design, data collection, data extraction, analysis, interpretation of findings, and final academic decisions, were conducted, reviewed, and approved by the authors. The authors take full responsibility for the accuracy, integrity, originality, and scholarly content of this manuscript.

10. DATA AVAILABILITY/SUPPLEMENTARY MATERIALS

The data and/or supplementary materials supporting the findings of this study are available from the corresponding author upon reasonable request, where applicable.

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11. ETHICS STATEMENT

The authors declare that this study did not involve human participants or animal subjects. Where applicable, all procedures were conducted in accordance with relevant institutional guidelines, safety requirements, and ethical standards.

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