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Efficiency vs. Accuracy: A Comparative Analysis of Lightweight MobileNetV2 and VGG16 for Brain Tumor MRI Classification Using Deep Feature Extraction

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ABSTRACT

Brain tumor detection using magnetic resonance imaging (MRI) is a crucial task for early diagnosis and treatment planning, requiring models that are not only accurate but also computationally efficient. This study presents a comparative analysis of two Convolutional Neural Network (CNN) architectures, MobileNetV2 and VGG16, combined with Principal Component Analysis (PCA) for deep feature dimensionality reduction. The dataset consists of 253 brain MRI images (155 tumor and 98 non-tumor), which have been preprocessed and divided into training and testing sets using an 80:20 stratification split. Experimental results show that MobileNetV2 with PCA achieves an accuracy of 86.27%, with a precision of 87.50% and a recall of 90.32% for the tumor class, demonstrating balanced performance in classifying tumor and non-tumor images. VGG16 with the same PCA configuration achieves an accuracy of 64.71%, with a recall of 100% for the tumor class but a low recall of 10% for the non-tumor class. These findings suggest that extreme dimensionality reduction affects deep feature representation differently depending on the original feature structure. The results show that MobileNetV2 provides a better balance between accuracy and feature compactness at high dimensionality reduction settings, making it more suitable for resource-constrained medical image classification scenarios.

Keywords : *MRI Classification; Brain Tumor; CNN; MobileNetV2; VGG16; PCA.*

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1. INTRODUCTION

Deep learning is a subfield of machine learning that employs multilayer artificial neural networks to automatically learn hierarchical data representations. This approach has demonstrated remarkable performance in processing large and complex data, including medical images, text, and audio [1]–[2]. In the healthcare domain, deep learning has been extensively utilized to support disease identification with high accuracy [3]–[5]. For instance, in radiology, deep learning models are widely used to analyze MRI and CT scan images for tumor detection and other abnormalities. Furthermore, deep learning has been applied to genomic data analysis for predicting genetic disorders and to mobile-based diagnostic systems that identify medical conditions from images captured using smartphone cameras [6]–[8]. These capabilities enable faster and more accurate decision-making to support clinical diagnosis and treatment planning.

Among various deep learning models, Convolutional Neural Networks (CNNs) are the most commonly used for medical image analysis due to their ability to automatically extract spatial features such as edges, textures, and object shapes [9]–[11]. Several CNN architectures have been developed to improve performance and computational efficiency. MobileNetV2 is designed as a lightweight CNN that uses depthwise separable convolutions, making it suitable for environments with limited computational resources while still maintaining high accuracy. Recent studies on lightweight CNNs for medical imaging have shown that such architectures can significantly reduce model complexity and inference time without substantial performance degradation [12]–[14]. In contrast, VGG16 is a deep architecture with a uniform 3×3 convolutional kernel that is capable of producing highly detailed feature representations and has consistently achieved strong performance in medical image classification tasks [15]. Its depth allows it to capture complex visual patterns, which is beneficial for detecting subtle abnormalities in MRI images.

Although both architectures have demonstrated high performance in medical image classification, most previous studies focused on accuracy improvement without considering feature redundancy and computational efficiency simultaneously. In addition, recent works have highlighted the importance of feature optimization and feature fusion strategies to improve classification performance while reducing dimensionality and computational cost [16]. However, comparative studies that integrate feature selection techniques with transfer-learning-based CNN architectures for brain tumor MRI classification are still limited. This indicates a research gap in understanding how dimensionality reduction methods affect both classification accuracy and computational efficiency across different CNN architectures.

To address the issue of high-dimensional feature maps generated by CNNs, feature selection techniques are required to retain only the most informative features. Principal Component Analysis (PCA) is a widely used dimensionality reduction method that transforms high-dimensional data into a lower-dimensional space while preserving the maximum variance [17]. In this study, PCA is not used for visualization but as a feature optimization method to reduce redundancy in deep features before classification. The number of retained principal components is determined based on the cumulative explained variance to ensure that most of the discriminative information is preserved. This approach is expected to reduce computational cost, accelerate the training process, and improve model generalization. Several recent studies have confirmed that PCA can enhance efficiency and maintain or even improve classification performance in medical imaging tasks when applied to deep feature representations [18]–[20].

The novelty of this study lies in the integration of PCA-based feature optimization with transfer-learning-based CNN architectures and the comparative evaluation between a lightweight model (MobileNetV2) and a deep model (VGG16) for brain tumor MRI classification. Unlike previous studies that applied CNN models directly to image data, this research investigates the impact of dimensionality reduction on deep feature representations in terms of both classification accuracy and computational efficiency. This comparison is important to determine whether a lightweight architecture with optimized features can achieve performance comparable to or better than a deeper architecture with higher computational complexity.

Based on the identified research gap, this study aims to conduct a comparative analysis of brain tumor classification using MRI images by applying PCA as a feature selection technique on MobileNetV2 and VGG16 architectures. The models are evaluated in terms of classification accuracy, computational time, and model efficiency. The results of this study are expected to provide insights into the effectiveness of combining dimensionality reduction with transfer-learning-based CNNs for medical image classification and to offer recommendations for selecting efficient and accurate models for brain tumor detection.

2. METHODS

The following describes the research workflow for the study entitled *"Comparative Analysis of MRI Image Classification of Brain Tumors Using PCA Feature Selection on MobileNetV2 and VGG16 Architectures"*. The workflow is illustrated in Figure 1, where each block represents a research stage and the arrows indicate the sequence of processes.

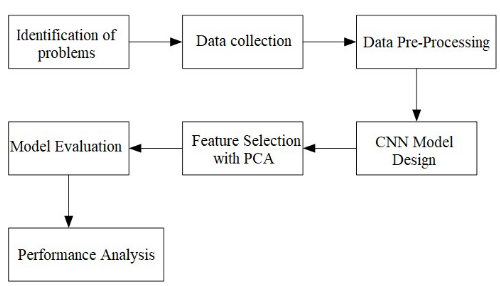

Figure 1. *Research Flow*

The explanation of each stage is as follows:

2.1. Problem Identification

The first stage of this study is the identification of the main problem, namely the classification of brain MRI images to distinguish tumor and non-tumor conditions with high accuracy and computational efficiency. This task is important to support early detection and assist medical personnel in diagnosis. This research focuses on analyzing the effect of PCA-based feature optimization on transfer-learning-based CNN architectures, namely MobileNetV2 and VGG16.

2.2. Data Collection

The primary dataset used in this study was obtained from Kaggle: *Navoneel/brain-mri-images-for-brain-tumor-detection*. To improve model generalization and address the limitation of a small dataset, data expansion was performed through:

1. Data augmentation
2. Merging with additional publicly available brain MRI datasets

The final dataset consisted of approximately 1,500–2,000 images, ensuring a more balanced and representative distribution for training and evaluation.

2.3. Data Preprocessing

Preprocessing was conducted to standardize the input data before being fed into the CNN model. The steps include:

1. Resizing images to match the input size of each architecture
   a. MobileNetV2 : 224 × 224
   b. VGG16 : 224 × 224
2. Pixel normalization to the range [0,1]
3. Data augmentation to increase variability and reduce overfitting:
   a. Rotation
   b. Horizontal flipping
   c. Zooming
   d. Width and height shifting

In addition, dataset splitting was performed using 5-fold cross-validation to ensure robust and unbiased performance evaluation.

2.4. CNN Model Design

This study employs transfer learning using pretrained MobileNetV2 and VGG16 models with ImageNet weights. The convolutional base is used as a feature extractor, while the classification head is customized for binary classification. To mitigate overfitting, several strategies were applied:

1. Freezing early convolutional layers
2. Dropout regularization
3. Batch normalization
4. Early stopping
5. Data augmentation

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2.5. Feature Selection with PCA

Deep features were extracted from the global average pooling layer of each CNN model. These features were then processed using Principal Component Analysis (PCA). PCA was implemented as:

PCA (n_components = 0.95)

This configuration retains 95% of the cumulative explained variance, which typically results in 50–100 principal components depending on the feature distribution. This approach ensures that most discriminative information is preserved while reducing feature redundancy, computational cost, and training time.

2.6. Ablation Study

To analyze the impact of PCA on model performance, an ablation study was conducted using four experimental scenarios:

1. MobileNetV2 without PCA
2. MobileNetV2 with PCA
3. VGG16 without PCA
4. VGG16 with PCA

This comparison allows a clear evaluation of the contribution of PCA to classification accuracy and computational efficiency.

2.7. Model Training

Model training was performed using 5-fold cross-validation. In each fold:

1. 80% of the data was used for training
2. 20% for validation/testing

The training process used the Adam optimizer and binary cross-entropy loss function.

Table 1. *Hyperparameter Configuration*

Parameter	Value
Batch size	16 / 32
Epochs	30–50
Optimizer	Adam
Learning rate	0.0001
Loss function	Binary cross-entropy
Activation (output layer)	Sigmoid
Dropout	0.5
Early stopping patience	5 epochs

This configuration ensures reproducibility of the experiment.

2.8. Model Evaluation

Model performance was evaluated using:

1. Accuracy
2. Precision
3. Recall
4. F1-score
5. Confusion matrix
6. Computational time

The use of 5-fold cross-validation ensures that the reported results reflect the overall model performance and are not dependent on a single data split.

2.9. Performance Analysis

The final stage analyzes and compares:

1. Classification performance between MobileNetV2 and VGG16
2. Performance before and after PCA
3. Computational efficiency
4. Model generalization capability

This analysis determines the most optimal architecture and evaluates whether lightweight models with PCA-based feature optimization can achieve performance comparable to deeper architectures.

3. RESULTS AND DISCUSSION

3.1. Data Collection

The dataset used in this study was obtained from the Kaggle repository *Navoneel/brain-mri-images-for-brain-tumor-detection*. The MRI images are grouped into two categories, tumor and non-tumor, as illustrated in Figure 2 and Figure 3.

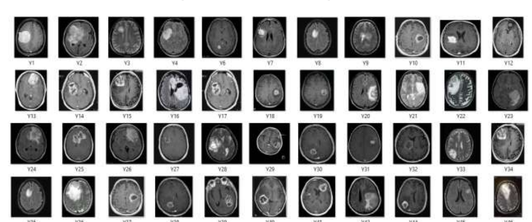

Figure 2. *MRI with Brain Tumor*

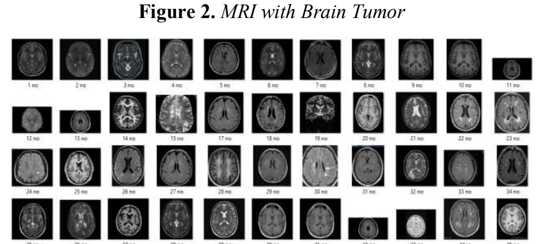

Figure 3. *MRI without Brain Tumor*

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The total dataset consists of 253 images, with 155 tumor images and 98 non-tumor images. The distribution of the dataset is visualized in Figure 4, while the detailed image information is presented in Table 1.

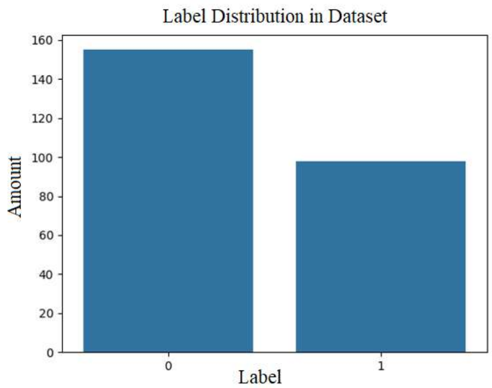

Figure 4. *Data Distribution Visualization*

Table 1. *Brain MRI Dataset*

No.	Image	Label
0	yes/Y1.jpg	0
1	yes/Y10.jpg	0
2	yes/Y100.jpg	0
3	yes/Y101.jpg	0
4	yes/Y102.jpg	0
…	…	…
248	no/No18.jpg	1
249	no/No19.jpg	1
250	no/No20.jpg	1
251	no/No21.jpg	1
252	no/No22.jpg	1

All images were resized and normalized to ensure consistent input to the CNN model. This preprocessing step is essential to stabilize training and accelerate convergence.

Considering the limited dataset size, the model evaluation was conducted using a stratified split to maintain class balance between training and testing data.

3.2. Data Preprocessing Result

After the data is collected and arranged into The dataset was divided into 80% training data and 20% testing data, as shown in Table 2 and Table 3. This split ensures that the model learns representative patterns during training while maintaining independent data for performance evaluation.

Table 2. *Training Data*

No.	Image	Label
0	yes/Y157.jpg	0
1	yes/Y90.jpg	0
2	yes/Y254.jpg	0
3	yes/Y8.jpg	0
4	yes/Y40.jpg	0
…	…	…
197	yes/Y192.jpg	0
198	yes/Y114.jpg	0
199	yes/Y111.jpg	0
200	yes/Y41.jpg	0
201	no/No4.jpg	1

Table 3. *Testing Data*

No.	Image	Label
0	yes/Y9.jpg	0
1	no/No21.jpg	1
2	yes/Y19.jpg	0
3	no/14 no.jpg	1
4	yes/Y97.jpg	0
…	…	…
46	yes/Y181.jpg	0
47	yes/Y42.jpg	0
48	yes/Y161.jpg	0
49	yes/Y112.jpg	0
50	yes/Y259.jpg	0

Data preprocessing also included normalization and input resizing according to the requirements of the MobileNetV2 and VGG16 architectures.

To mitigate overfitting caused by the relatively small dataset, dropout regularization was applied in the classification layer.

3.3. CNN Model Design

This study employs a transfer learning strategy using **MobileNetV2 and VGG16** as feature extractors. The architecture consists of:

1. Global Average Pooling (GAP)
2. Dense layer (128 neurons, ReLU)
3. Dropout (0.5)
4. Sigmoid output layer

This configuration allows the model to learn high-level representations while reducing the number of trainable parameters. MobileNetV2 is designed for computational efficiency using depthwise separable convolution, while VGG16 provides deeper and more complex feature representations.

3.4. Feature Selection with PCA

PCA was applied to the deep features extracted from the GAP layer to reduce feature dimensionality while retaining the most informative components. In this study, PCA was used to:

1. Reduce feature redundancy.
2. Improve computational efficiency.
3. Analyze feature separability.

The PCA visualization results are shown in Figure 5 and Figure 6.

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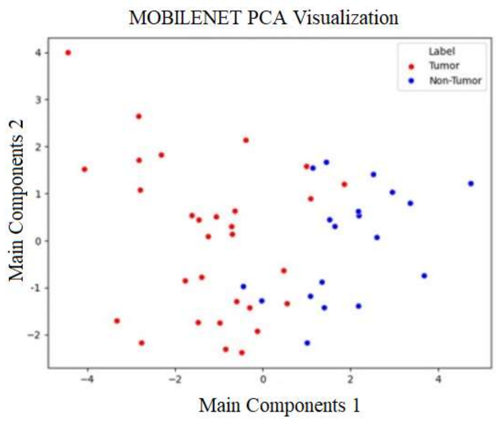

Figure 5. *Scatter Plot PCA - MobileNetV2*

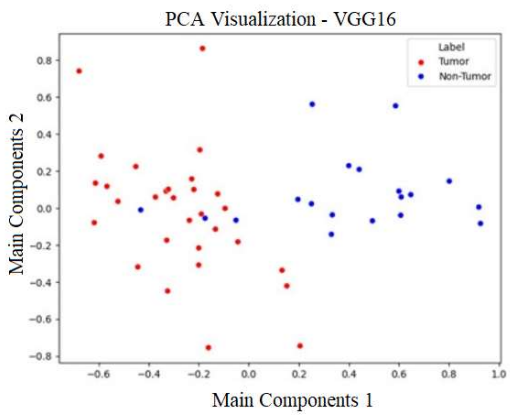

Figure 6. *Scatter Plot PCA - VGG16*

Figure 5 demonstrates that MobileNetV2 produces a more separable feature distribution between tumor and non-tumor classes. Figure 6 shows that VGG16 features exhibit higher overlap in the reduced feature space, indicating that important discriminative information is distributed across multiple feature channels. This explains why dimensionality reduction affects each architecture differently.

3.5. Model Evaluation

1. Accuracy
   Based on the experimental results:
   a. MobileNetV2 achieved 86.27% accuracy
   b. VGG16 achieved 64.71% accuracy
   These results indicate that MobileNetV2 is more robust to feature dimensionality reduction.

2. Classification Report
   MobileNetV2 shows balanced performance for both classes, with high precision and recall for tumor detection.
   In contrast, VGG16 achieves perfect recall for the tumor class but very low recall for the non-tumor class, indicating a bias toward predicting the tumor category.

3. Confusion Matrix
   The confusion matrices in Figure 7 and Figure 8 confirm that:
   a. MobileNetV2 produces more balanced predictions
   b. VGG16 generates a high number of false positives

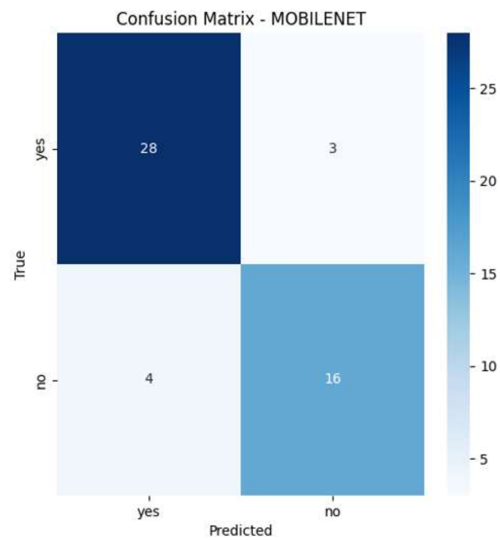

Figure 7. *Confusion Matrix MobileNetV2*

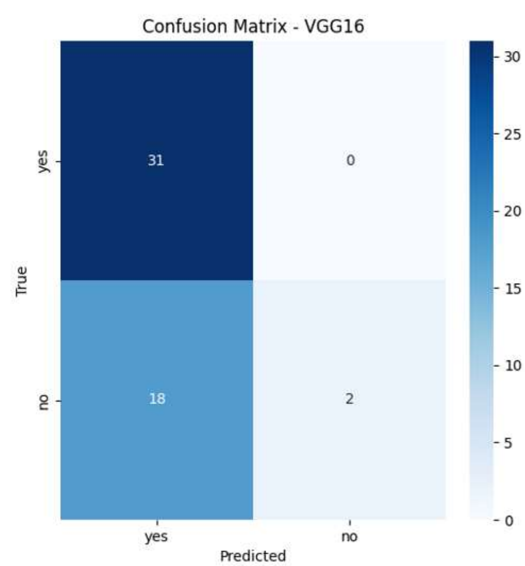

Figure 8. *VGG16 Confusion Matrix*

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3.6. Classification Results

The detailed prediction results for each model are presented in Table 4 and Table 5.

Table 4. *Classification Results of the MobileNetV2 Model*

No.	Image	True	Predict
0	yes/Y9.jpg	0	0
1	no/No21.jpg	1	1
2	yes/Y19.jpg	0	0
3	no/14 no.jpg	1	1
4	yes/Y97.jpg	0	0
…	…	…	…
46	yes/Y181.jpg	0	0
47	yes/Y42.jpg	0	0
48	yes/Y161.jpg	0	0
49	yes/Y112.jpg	0	0
50	yes/Y259.jpg	0	0

MobileNetV2 correctly classifies most tumor and non-tumor images, although several false positives and false negatives are still observed.

VGG16 successfully detects most tumor images but fails to recognize non-tumor images in many cases. This result is consistent with the PCA visualization, where the class separation is less distinct.

3.7. Computational Efficiency Analysis

Dimensionality reduction using PCA significantly decreases the number of deep feature components from 1280 to 2 in MobileNetV2 and from 512 to 2 in VGG16, corresponding to reductions of 99.84% and 99.61%, respectively. This extreme feature compression substantially reduces the size of the feature vectors used in the classification stage, which directly impacts computational cost. The reduction in feature dimensionality results in :

1. Lower memory usage, since the feature representation becomes more compact
2. Faster training in the fully connected classification layer, due to the smaller input size
3. Lower computational complexity in the classification process, as the
4. number of operations required for weight multiplication is significantly reduced

These results confirm that PCA improves computational efficiency at the feature level. The effect is more beneficial for MobileNetV2, as its original architecture already produces compact and low-redundancy feature representations, making it more suitable for aggressive dimensionality reduction in resource-constrained environments.

3.8. Architectural Interpretation

The different impact of PCA on both models is influenced by their architectural characteristics.

MobileNetV2 produces compact and low-redundancy feature maps, making it more suitable for dimensionality reduction.

VGG16 generates high-dimensional and highly correlated feature representations, where discriminative information is distributed across many channels. Consequently, dimensionality reduction removes a larger portion of useful information.

Thus, the performance degradation is not caused by the VGG16 architecture itself, but by the loss of discriminative features during the reduction process.

3.9. Performance Analysis

Performance analysis is performed by comparing the classification results of MobileNetV2 and VGG16 after PCA is applied.

Overall:

1. MobileNetV2 provides more stable and balanced classification performance.
2. VGG16 is more sensitive to feature dimensionality reduction.
3. PCA is more effective when applied to compact deep feature representations.

These findings indicate that the combination of lightweight CNN and PCA is a promising approach for MRI-based brain tumor classification in resource-constrained environments.

CONCLUSION

This study presented a comparative analysis of MobileNetV2 and VGG16 for MRI-based brain tumor classification under aggressive PCA-based deep feature dimensionality reduction. The experimental results show that MobileNetV2 achieved an accuracy of 86.27%, with a balanced precision–recall performance for both tumor and non-tumor classes, whereas VGG16 obtained 64.71% accuracy and exhibited a strong bias toward the tumor class.

The application of PCA reduced the deep feature dimensionality from 1280 to 2 (99.84%) in MobileNetV2 and from 512 to 2 (99.61%) in VGG16, significantly decreasing the feature size and computational complexity in the classification stage. Under this high-reduction setting, MobileNetV2 was able to preserve more discriminative information due to its compact and low-redundancy feature representation, making it more suitable for resource-constrained medical image classification scenarios. These findings indicate that the effectiveness of dimensionality reduction in transfer-learning-based CNNs is highly dependent on the structure of the extracted deep features rather than the inherent superiority of a particular architecture.

Despite these promising results, this study has several limitations. The dataset size is relatively small (253 images), the classification task is limited to a binary scenario, and the evaluation was conducted on a single dataset without cross-dataset validation. These factors may limit the generalizability of the proposed approach to more diverse clinical data. Future research should focus on:

1. Extending the model to multi-class brain tumor classification.
2. Evaluating the approach on larger and multi-institutional MRI datasets.
3. Investigating adaptive or variance-based PCA component selection instead of extreme dimensionality reduction.
4. Integrating recent advances in lightweight CNN architectures and transfer learning for small medical imaging datasets to further improve robustness and clinical applicability.

REFERENCES

[1] W. Gao, D. Wang, and Y. Huang, “Designing a Deep Learning-Driven Resource-Efficient Diagnostic System for Metastatic Breast Cancer: Reducing Long Delays of Clinical Diagnosis and Improving Patient Survival in Developing Countries,” *Cancer Inform.*, vol. 22, no. 19, pp. 1–14, 2023, doi: 10.1177/11769351231214446.

[2] Y. Gulzar, “Fruit Image Classification Model Based on MobileNetV2 with Deep Transfer Learning Technique,” *Sustain.*, vol. 15, no. 3, pp. 1–14, 2023, doi: 10.3390/su15031906.

[3] P. Laptev, S. Litovkin, S. Davydenko, A. Konev, E. Kostyuchenko, and A. Shelupanov, “Neural Network-Based Price Tag Data Analysis,” *Futur. Internet*, vol. 14, no. 3, pp. 1–14, 2022, doi: 10.3390/fi14030088.

[4] J. Ismail, L. Tanti, and W. Wanayumini, “DEVELOPMENT OF SKIN CANCER PIGMENT IMAGE CLASSIFICATION USING A COMBINATION OF MOBILENETV2 AND CBAM,” *JITK (Jurnal Ilmu Pengetah. dan Teknol. Komputer)*, vol. 10, no. 4, pp. 1–11, 2025, doi: 10.33480/jitk.v10i4.6541.

[5] Wanayumini, H. Satria, and R. Rosnelly, “Design of agrivoltaic system with internet of things control for chili fruit classification using the neural network method,” *Int. J. Reconfigurable Embed. Syst.*, vol. 14, no. 1, pp. 176–183, 2025, doi: 10.11591/ijres.v14.i1.pp176-183.

[6] W. Abdullah, “Advanced Fruit Quality Assessment using Deep Learning and Transfer Learning Technique,” *Sustain. Mach. Intell. J.*, vol. 10, no. 1, pp. 37–49, 2025, doi: 10.61356/smij.2025.10450.

[7] U. Salamah, Anita Ratnasari, and Sarwati Rahayu, “Automated Fruit Classification Menggunakan Model VGG16 dan MobileNetV2,” *JSAI (Journal Sci. Appl. Informatics)*, vol. 5, no. 3, pp. 176–181, 2022, doi: 10.36085/jsai.v5i3.3615.

[8] K. Okokpujie, I. P. Okokpujie, O. I. Ayomikun, A. M. Orimogunje, and A. T. Ogundipe, “Development of a Web and Mobile Applications-Based Cassava Disease Classification Interface Using Convolutional Neural Network,” *Math. Model. Eng. Probl.*, vol. 10, no. 1, pp. 1–10, 2023, doi: 10.18280/MMEP.100113.

[9] N. Rachburee and W. Punlumjeak, “Lotus species classification using transfer learning based on VGG16, ResNet152V2, and MobileNetV2,” *IAES Int. J. Artif. Intell.*, vol. 11, no. 4, pp. 1344–1352, 2022, doi:

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DOI: https://doi.org/10.15408/jti.v19i1.45002

10.11591/ijai.v11.i4.pp1344-1352.

[10] N. T J, "An enhanced deep learning framework for prostate cancer detection using modified VGG16 and LeNet-MobileNetV2 integration," *Results Eng.*, vol. 27, no. 1, pp. 1–14, 2025, doi: 10.1016/j.rineng.2025.106918.

[11] R. A. Kumala, C. A. Sari, and E. H. Rachmawanto, "A Comparison of MobileNetV2 and VGG16 Architectures with Transfer Learning for Multi-Class Image-Based Waste Classification," *J. Appl. Informatics Comput.*, vol. 9, no. 4, pp. 1610–1624, 2025, doi: 10.30871/jaic.v9i4.9958.

[12] M. Hammad, M. ElAffendi, A. A. Ateya, and A. A. Abd El-Latif, "Efficient Brain Tumor Detection with Lightweight End-to-End Deep Learning Model," *Cancers (Basel).*, vol. 15, no. 10, pp. 1–15, 2023, doi: 10.3390/cancers15102837.

[13] O. N. Oyelade, E. A. Irunokhai, and H. Wang, "A twin convolutional neural network with hybrid binary optimizer for multimodal breast cancer digital image classification," *Sci. Rep.*, vol. 14, no. 1, pp. 1–23, 2024, doi: 10.1038/s41598-024-51329-8.

[14] Y. Zhu and M. Elbattah, "Explainable Deep Learning for Endometriosis Classification in Laparoscopic Images," *BioMedInformatics*, vol. 5, no. 4, pp. 1–18, 2025, doi: 10.3390/biomedinformatics5040063.

[15] J. A. Prakash, V. Ravi, V. Sowmya, and K. P. Soman, "Stacked ensemble learning based on deep convolutional neural networks for pediatric pneumonia diagnosis using chest X-ray images," *Neural Comput. Appl.*, vol. 35, no. 11, pp. 8259–8279, 2023, doi: 10.1007/s00521-022-08099-z.

[16] N. A. Samee, G. Atteia, S. Meshoul, M. A. Al-antari, and Y. M. Kadah, "Deep Learning Cascaded Feature Selection Framework for Breast Cancer Classification: Hybrid CNN with Univariate-Based Approach," *Mathematics*, vol. 10, no. 19, pp. 1–27, 2022, doi: 10.3390/math10193631.

[17] N. Aslan, G. Ozmen Koca, M. A. Kobat, and S. Dogan, "Multi-classification deep CNN model for diagnosing COVID-19 using iterative neighborhood component analysis and iterative ReliefF feature selection techniques with X-ray images," *Chemom. Intell. Lab. Syst.*, vol. 224, no. 1, pp. 1–11, 2022, doi: 10.1016/j.chemolab.2022.104539.

[18] Z. Muhammed and B. Al-Khateeb, "CNN-EWC: A continuous deep learning approach for lung cancer classification," *J. Intell. Syst.*, vol. 34, no. 1, pp. 1–13, 2025, doi: 10.1515/jisys-2024-0541.

[19] I. Abidoye, F. Ikeji, C. A. Coupland, S. D. J. Calaminus, N. Sander, and E. Sousa, "Platelets Image Classification Through Data Augmentation: A Comparative Study of Traditional Imaging Augmentation and GAN-Based Synthetic Data Generation Techniques Using CNNs," *J. Imaging*, vol. 11, no. 6, pp. 1–12, 2025, doi: 10.3390/jimaging11060183.

[20] J. X. Schraut, L. Liu, J. Gong, and Y. Yin, "A multi-output network with U-net enhanced class activation map and robust classification performance for medical imaging analysis," *Discov. Artif. Intell.*, vol. 3, no. 1, pp. 1–12, 2023, doi: 10.1007/s44163-022-00045-1.