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Research Article

Classification of Cavendish Banana Maturity with CNN Method ResNet50 architecture

Tjokorda Istri Agung Pandu Yuni Maharani [1,*], I Gusti Agung Indrawan [2], Gede Dana Pramitha [3], Christina Purnama Yanti [4], I Made Marthana Yusa [5]

[1] Institut Bisnis dan Teknologi Indonesia, Denpasar, Bali 80225, Indonesia, yunimaha20@gmail.com
[2] Institut Bisnis dan Teknologi Indonesia, Denpasar, Bali 80225, Indonesia, agung.indrawan@instiki.ac.id
[3] Institut Bisnis dan Teknologi Indonesia, Denpasar, Bali 80225, Indonesia, danagede@instiki.ac.id
[4] Institut Bisnis dan Teknologi Indonesia, Denpasar, Bali 80225, Indonesia, christinapy@instiki.ac.id
[5] Institut Bisnis dan Teknologi Indonesia, Denpasar, Bali 80225, Indonesia, made.marthana@instiki.ac.id

Correspondence should be addressed to Tjokorda Istri Agung Pandu Yuni Maharani; yunimaha20@gmail.com

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Abstract:

The Cavendish banana is a tropical fruit that is widely consumed in Indonesia due to its sweet taste and high nutritional content. However, the degree of ripeness of a banana has a direct effect on its sugar content, which can be of particular concern for diabetics. The riper the banana, the higher the content of simple sugars such as glucose, fructose, and sucrose, which can increase the glycemic index (GI) and trigger blood sugar spikes. To assist diabetics in selecting bananas according to their ripeness level, this study developed a Cavendish banana ripeness classification model based on ResNet50 Convolutional Neural Network (CNN) architecture.The research was conducted by collecting 475 images of Cavendish bananas from plantations in Jembrana, Bali, which were classified into five ripeness categories based on skin color. The dataset was expanded to 2,375 images through data augmentation techniques, such as rotation, flip, zoom, and translation. The ResNet50 model was modified by adding several new layers and optimized using Adam and SGD algorithms with varying learning rates. Evaluation was performed through different training scenarios and using the K-fold validation method.The results showed that the best scenario was achieved when using augmented data, Adam's optimizer, and a learning rate of 0.0001, which resulted in accuracies of up to 99% and 98% after cross-validation.In comparison, the model without augmentation only achieved a maximum accuracy of 81%. Thus, the use of the ResNet50 model proved to be effective for Cavendish banana ripeness classification.

Keywords: Augmentation, Classification, CNN, k-fold cross-validation , ResNet50.

1. Introduction

The banana is a tropical fruit that is widely loved by people around the world, including in Indonesia. Apart from their sweet taste and soft texture, bananas are rich in nutrients such as vitamins, minerals, and fiber that are beneficial for health [1], [2]. Among the various types of bananas, Cavendish is one of the most popular varieties due to its wide availability and consistent flavor quality. In Indonesia, Cavendish bananas are available in various stages of ripeness, from unripe to fully ripe [3], [4].

However, the consumption of bananas at certain levels of ripeness may be of particular concern for diabetics. Based on data from the International Diabetes Federation (IDF) in 2021, the number of people with diabetes in Indonesia reached 19.5 million, making it one of the countries with the highest prevalence of diabetes in the world [5]. Ripe bananas are known to have a higher natural sugar content than unripe bananas. During the ripening process, the starch in the banana turns into simple sugars such as glucose, fructose, and sucrose, thus increasing the glycemic index (GI). This can cause a spike in blood sugar levels, which is risky for diabetics [6], [7], [8]. Diabetics can still consume bananas, but with some important considerations, especially related to the ripeness of the banana. This is because bananas, especially ripe ones, contain higher levels of natural sugars, such as glucose, fructose, and sucrose, which can increase blood sugar levels. The riper the banana, the higher the simple sugar content, thus affecting the glycemic index (GI) of the banana [9], [10]. Therefore, managing the consumption of bananas based on their ripeness level is an important requirement to help diabetics maintain stable blood sugar levels [11], [12], [13].

On the other hand, recent developments in artificial intelligence (AI) technology, particularly in the field of image recognition, offer innovative solutions to address this problem [14]. One AI method that has proven effective is Convolutional Neural Network (CNN), which is a deep learning algorithm designed to automatically recognize patterns and features in images [15], [16]. CNNs work by convolving the input image using filters or kernels to extract important features, such as edges, texture, and shape [17]. This process allows the model to learn to recognize objects and patterns in the image without requiring manual programming of features.

One popular CNN architecture is ResNet50, which stands for “Residual Networks” with 50 layers [18], [19]. ResNet50 is designed to overcome the vanishing gradient problem that often occurs in deep neural networks [20], [21], [22]. By utilizing this architecture, the system can analyze the visual characteristics of Cavendish bananas, such as skin color and texture, to determine their ripeness level quickly and accurately [23], [24]. CNN-based models, especially those using architectures such as ResNet50, have great potential to provide more efficient and precise solutions for diabetics in selecting bananas with ripeness levels that suit their needs.

Currently, there are not many classification models devoted to Cavendish banana ripeness classification, especially those designed to help diabetics control sugar intake. This research aims to develop a ResNet50 architecture model that can accurately classify the ripeness level of Cavendish bananas. This model is expected to not only be a practical solution for people, especially diabetics, in choosing bananas that suit their needs but also to be used as a reference for the development of similar systems in the future.

2. Method:

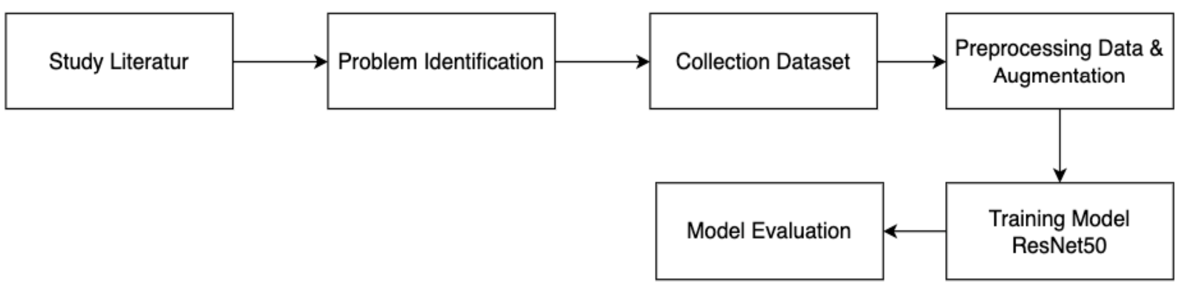

Figure 1. Research Flow

This research process begins with a literature study to review various previous studies and theories relevant to the topic of classification of Cavendish banana maturity levels. The next stage is problem identification, which determines the main problem that becomes the focus of the research. After that, data collection is carried out, which involves methods such as observation, interviews, and documentation to obtain relevant data. The collected data then went through preprocessing and data augmentation stages to ensure the data was ready to be used in the next process and augmentation to add variety to the data. In the next stage, the ResNet50 model is trained to evaluate the model's performance in classifying banana ripeness levels. Finally, results analysis and conclusions are conducted, where test results are analyzed to determine the extent to which the model is able to provide accurate classification results.

Data Selection

This study used primary data collected from Cavendish banana plantations in the Jembrana region of Bali. Images were captured using an iPhone 11 cell phone camera with 12 MP resolution. The objects were Cavendish banana fruits classified into five color-based ripeness categories, namely: green, yellowish green, yellow, spotted yellow, and spotted brownish yellow. The total number of images collected is 475. After data augmentation, the total dataset increased to 2.375 images.

Figure 2. (A) green, (B) yellowish green, (C) yellow, (D) spotted yellow, (E) spotted brownish yellow.

Tools and Technology

This research utilizes technologies and tools to train, build, and evaluate models namely:

a. Program language: Python
b. ReLU activation function
c. Trained Models: ResNet50
d. Adam & SGD optimizer
e. Deep Learning Framework: TensorFlow and Keras
f. K-fold cross-validation

Data Pre-processing and Augmentation

The data preprocessing stage begins with the division of the raw dataset into two main subsets, namely 80% training data and 20% validation data. This research dataset consists of five categories of Cavendish banana ripeness levels, namely green, yellowish green, yellow, spotted yellow, and spotted brownish yellow. In addition, all images were converted to a standard size of 224 × 224 pixels to meet the needs of the ResNet50 model. In this study, data is augmented with geometric transformation techniques, such as rotation, vertical flip, horizontal flip, zoom, and translation. These methods add variety to the appearance of objects in the dataset so that the model can recognize objects better even when viewed from different angles, sizes, or directions.

Model ResNet50

The CNN model architecture used in this research utilizes transfer learning with ResNet50 as the base model [25]. ResNet50 was chosen due to its superior ability in visual feature extraction from image data, based on its training on the ImageNet dataset[26], [27], [28]. The model was modified by adding several new layers to support banana ripeness classification. These layers include a global average pooling layer to reduce the feature dimension without losing key information, a dense layer with 1024 neurons and a ReLU activation function, and a dropout layer with a 50% dropout ratio to reduce the risk of overfitting [29], [30], [31]. Finally, the model has an output layer with five neurons and a softmax activation function for multi-class classification. With this architecture, the model is trained using the categorical crossentropy method for multi-class classification and optimized using Adam, which has the advantage of learning rate adjustment. This whole process allows the model to efficiently learn and adapt to the specific image dataset while utilizing the existing knowledge from the pre-trained model.

Data Analysis Method

The evaluation results of this study aim to determine the best combination of data usage and model settings in training. Several scenarios were tested, both using the original data (without augmentation) and data that had been augmented with geometric transformations such as rotation, flip, zoom, and translation. The aim is to see if augmentation can help the model recognize objects better in a variety of views. In addition, the evaluation also compares two optimization algorithms, namely Adam and SGD, to find out which one is more effective in the model training process. Also, the effect of the learning rate value was analyzed, by comparing two values, namely 0.0001 and 0.00001.

3. Results and Discussion

Results

Table 1. Evaluation Results of ResNet50 Models

Model	Data	Learning Rate	Optimizer	Accuracy	Accuracy With K-fold cross validation
ResNet50	Non Augmentasi	0.0001	SGD	0.77	0.81
		0.0001	Adam	0.73	
		0.00001	SGD	0.36	
		0.00001	Adam	0.65	
	Augmentasi	0.0001	SGD	0.97	0.98
		0.0001	Adam	0.99	
		0.00001	SGD	0.72	
		0.00001	Adam	0.98	

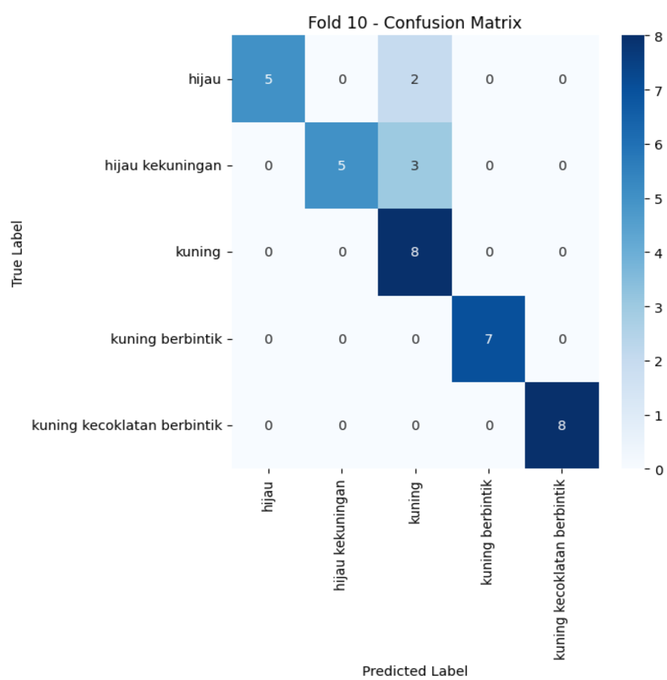

Figure 3. Confusion Matrix Non-Augmentation

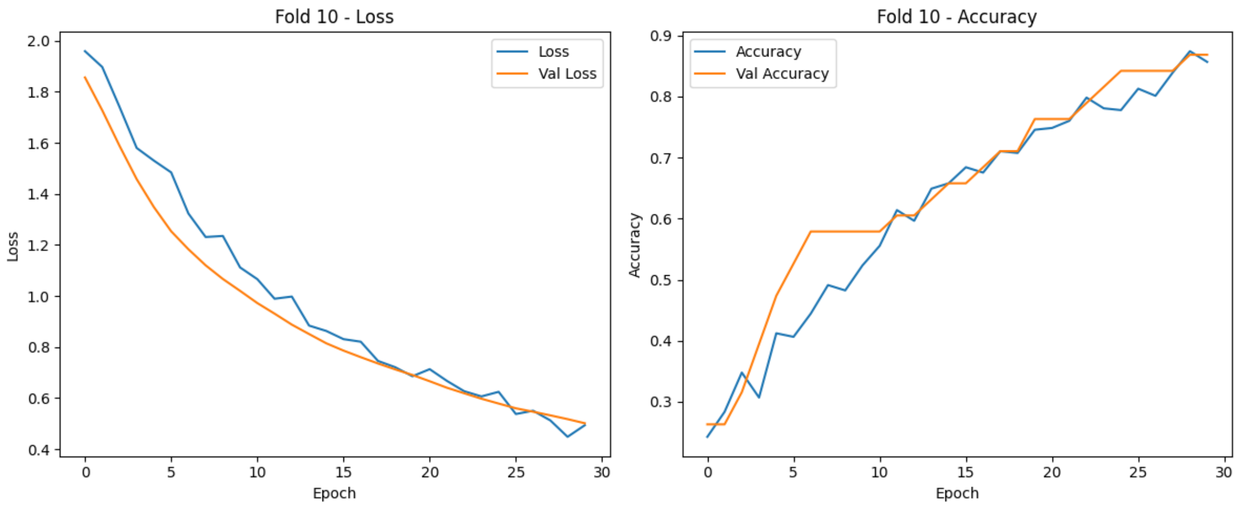

Figure 4. Accuracy and Loss Non-Augmentation

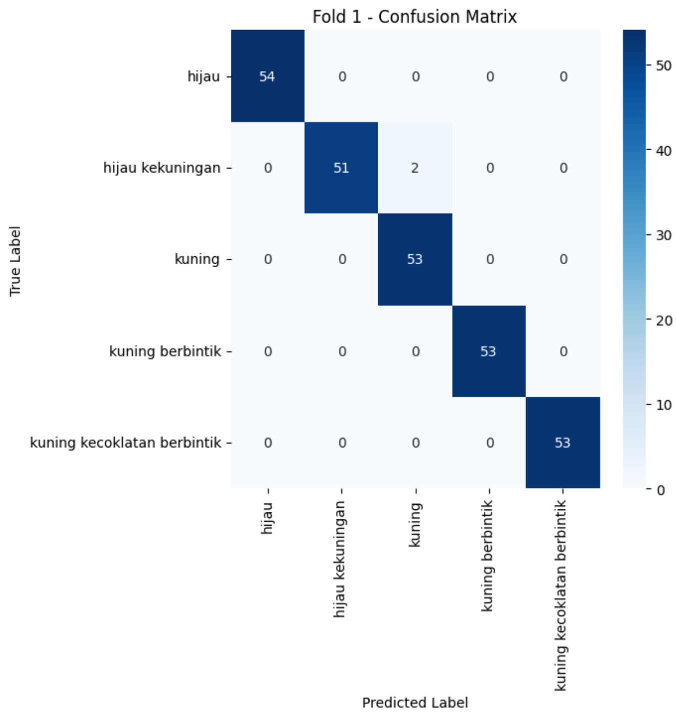

Figure 5. Confusion Matrix Augmentation

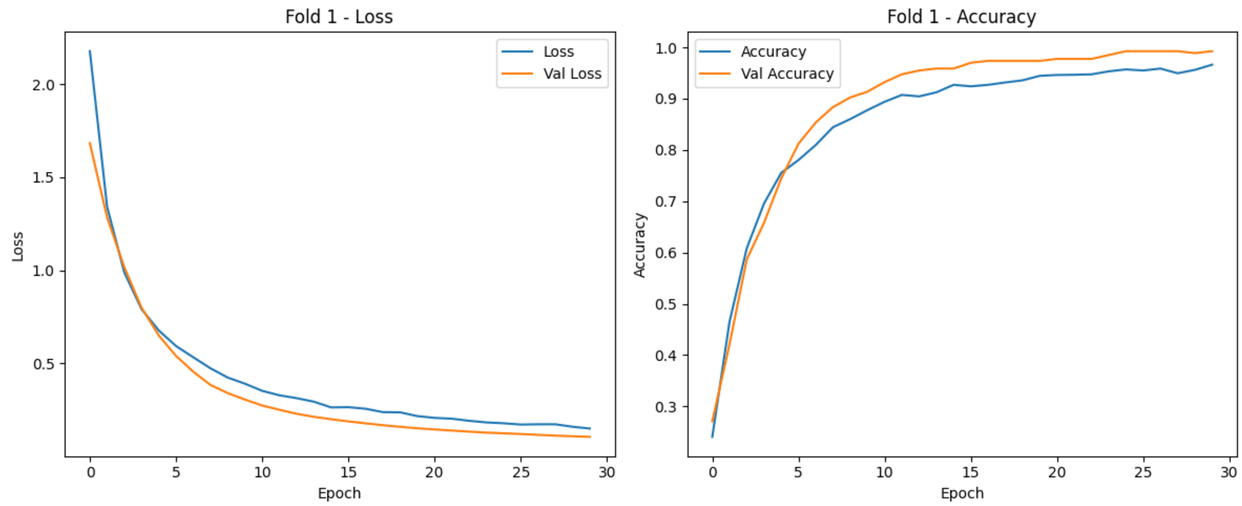

Figure 6. Accuracy and Loss Augmentation

Discussion

Based on the results shown in **Table 1**, the ResNet50 model shows varying performance in the eight training scenarios. ResNet50 model in the first scenario without data augmentation, using the SGD optimizer with a learning rate of 0.0001 got an accuracy of 0.77, in the second scenario without data augmentation, using the Adam optimizer with a learning rate of 0.0001 got an accuracy of 0.73, in the third scenario without data augmentation, using the SGD optimizer with a learning rate of 0.00001 got an accuracy of 0.36, in the fourth scenario without data augmentation, using the Adam optimizer with a learning rate of 0. 00001 gets an accuracy of 0.65, while in the fifth scenario with data augmentation, using the SGD optimizer with a learning rate of 0.0001 gets an accuracy of 0.97 in the sixth scenario with data augmentation, using the Adam optimizer with a learning rate of 0.0001 gets an accuracy of 0. 99, in the seventh scenario with data augmentation, using the SGD optimizer with a learning rate of 0.00001 got an accuracy of 0.72, in the eighth scenario with data augmentation, using the Adam optimizer with a learning rate of 0.00001 got an accuracy of 0.98, After all scenarios are tested, a K-Fold cross-validation process is carried out. The average accuracy result without data augmentation is 0.81, while with data augmentation it reaches 0.98.

4. Conclusion

This study shows that the ResNet50 CNN architecture is able to provide the best performance in classifying the ripeness level of Cavendish banana fruit, especially in scenarios that use data augmentation techniques. Optimal performance is achieved when the model is trained using the Adam optimizer with a learning rate of 0.0001 and validated using the K-Fold cross-validation method. In this scenario, the data used was augmented from 475 original images to a total of 2,375 Cavendish banana images. The test results show that the average accuracy obtained using data augmentation reaches 98%, much higher than the 81% accuracy obtained without augmentation. These results confirm that the application of data augmentation techniques is very effective in improving the performance of image classification models.

References:

[1] R. F. Rahayuniati, R. E. K. Kurniawan, and E. Mugiastuti, “Distribution of banana Fusarium wilt in Banyumas, Indonesia, and characterization of F. oxysporum isolates from infected bananas and taro growing on the same farm,” *Biodiversitas*, vol. 25, no. 4, pp. 1344–1351, 2024, doi: 10.13057/biodiv/d250401.

[2] an Fauzi Sekolah Tinggi Ilmu Tarbiyah Nahdlatul Ulama Al-Hikmah Mojokerto, I. Corresponding Author, and an Fauzi, “Civil Officium: Journal of Empirical Studies on Social Science Community Empowerment through Training on Making Various Flavored Cavendish Banana Chips to Improve the Community Economy”, doi: 10.53754/civilofficium.

[3] A. A. Suryani, U. Athiyah, Y. S. R. Nur, and Warto, "Classification of Cavendish Banana Quality using Convolutional Neural Network," *Transactions on Informatics and Data Science*, vol. 1, no. 1, pp. 1–10, Aug. 2024, doi: 10.24090/tids.v1i1.12191.

[4] A. Suparno, R. H. R Tanjung, L. Iriana Zebua, and S. Prabawardani, "Morphological diversity, ethnobotany, and economic value of banana plants (Musa spp.) in the Keerom lowland area, Papua Province, Indonesia," *ASIAN JOURNAL OF AGRICULTURE*, vol. 9, no. 1, 2025, doi: 10.13057/asianjagric/g090123.

[5] R. M. Sinaga and I. A. Ahmed, "Knowledge of Compliance in Taking Medication for Patients with Type 2 Diabetes Mellitus and Hypertension: A Review," *International Journal of Biotechnology and Biomedicine*, vol. 1, 2024, doi: 10.31674/ijbb.2024.v01i04.003.

[6] Béda Frank YAPO *et al.*, "Impact of ripening stage on the nutritional and antioxidant potential of fruit consumed by diabetics at the Abidjan Anti-Diabetic Centre," *World Journal of Advanced Research and Reviews*, vol. 22, no. 3, pp. 427–437, Jun. 2024, doi: 10.30574/wjarr.2024.22.3.1654.

[7] Y. Sun, J. Cheng, S. Cheng, and T. A. G. Langrish, "Multifilm Mass Transfer and Reaction Rate Kinetics in a Newly Developed In Vitro Digestion System for Carbohydrate Digestion," *Foods*, vol. 14, no. 4, Feb. 2025, doi: 10.3390/foods14040580.

[8] R. Ananta Burhan, T. Yuliarni, A. Baso Kaswar, and D. Darma Andayani, "Classification Of Sugar Levels In Banana Fruit Based On Color Features Using Digital Image Processing-Based Artificial Neural Networks," vol. 5, no. 4, pp. 1137–1145, 1420, doi: 10.52436/1.jutif.2024.5.4.1420.

[9] M. Mirzaei, M. H. Sharifi, S. Mahboobi, H. Shahinfar, M. Karimi, and M. H. Eftekhari, "The Relationship between Glycemic Index, Social Support and Sleep Quality in Patients with Type 2 Diabetes," *International Journal of Nutrition Sciences*, vol. 10, no. 2, pp. 126–135, Mar. 2025, doi: 10.30476/ijns.2025.100845.1286.

[10] S. I. Kuala, E. Juliastuti, and F. M. Dwivany, "Manufacture and Performance Test of Banana Ripe Detection Tool Using Laser Light Backscattering Imaging," in *AIP Conference Proceedings*, American Institute of Physics Inc., Feb. 2024. doi: 10.1063/5.0184012.

[11] K. M. S. Callaghan and U. Martinez-Hernandez, "Low-Cost, Multi-Sensor Non-Destructive Banana Ripeness Estimation Using Machine Learning," *IEEE Sens J*, 2025, doi: 10.1109/JSEN.2025.3528250.

[12] A. Nandabaram, V. K. Nelson, and V. Mayasa, "Assessment of Possible Food-Drug Interactions of Pearl Millet Diet on Gliclazide in Diabetic Rats," *Texila International Journal of Public Health*, vol. 13, no. 1, Mar. 2025, doi: 10.21522/TIJPH.2013.13.01.Art058.

[13] J.-B. Gbakayoro *et al.*, "Impact of Therapeutic Nutritional Education on the Anthropometric and Metabolic Parameters of Diabetic Subjects Monitored at the Smires Medical Center in Abidjan," *International Journal of Nutrition and Food Sciences*, vol. 2025, no. 1, pp. 22–27, doi: 10.11648/j.ijnfs.20251401.13.

[14] Satyadhar Joshi, "Retraining US Workforce in the Age of Agentic Gen AI: Role of Prompt Engineering and Up-Skilling Initiatives," *International Journal of Advanced Research in Science, Communication and Technology*, pp. 543–557, Feb. 2025, doi: 10.48175/IJARSCT-23272.

[15] M. M. Abd Zaid, A. A. Mohammed, and P. Sumari, "Classification of Road Features Using Convolutional Neural Network (CNN) and Transfer Learning," *International Journal of Computing and Digital Systems*, vol. 17, no. 1, 2025, doi: 10.12785/ijcds/1571031764.

[16] H. Wei, Y. Wang, Y. Sun, J. Zheng, and X. Yu, "A Joint Network of 3D-2D CNN Feature Hierarchy and Pyramidal Residual Model for Hyperspectral Image Classification," *IEEE Access*, 2025, doi: 10.1109/ACCESS.2025.3532016.

[17] A. A. Elngar *et al.*, "Image Classification Based On CNN: A Survey," *Journal of Cybersecurity and Information Management (JCIM)*, vol. 6, no. 1, p. 18, 2021, doi: 10.5281/zenodo.4897990.

[18] Y. Pan *et al.*, "Fundus image classification using Inception V3 and ResNet-50 for the early diagnostics of fundus diseases," *Front Physiol*, vol. 14, 2023, doi: 10.3389/fphys.2023.1126780.

[19] M. Elpeltagy and H. Sallam, "Automatic prediction of COVID− 19 from chest images using modified ResNet50," *Multimed Tools Appl*, vol. 80, no. 17, pp. 26451–26463, Jul. 2021, doi: 10.1007/s11042-021-10783-6.

[20] M. Talele and R. Jain, "A Comparative Analysis of CNNs and ResNet50 for Facial Emotion Recognition," *Engineering, Technology and Applied Science Research*, vol. 15, no. 2, pp. 20693–20701, Apr. 2025, doi: 10.48084/etasr.9849.

[21] "JITE (Journal of Informatics and Telecommunication Engineering) Implementation of Transfer Learning on CNN using DenseNet121 and ResNet50 for Brain Tumor Classification", doi: 10.31289/jite.v8i2.13952.

[22] J. Isohanni, "Customised ResNet architecture for subtle color classification," *International Journal of Computers and Applications*, 2025, doi: 10.1080/1206212X.2025.2465727.

[23] P. H. Huang *et al.*, "Changes in Nutrient Content and Physicochemical Properties of Cavendish Bananas var. Pei Chiao during Ripening," *Horticulturae*, vol. 10, no. 4, Apr. 2024, doi: 10.3390/horticulturae10040384.

[24] E. Shavna Gracia, N. Anisa Sri Winarsih, and D. Nuswantoro, "Comparison of VGG16, MobileNetV2, InceptionV3, ResNet50, and Custom CNN Architectures for Furniture Image Classification," vol. 16, no. 01, 2025, doi: 10.35970/infotekmesin.v16i1.2500.

[25] F. Javed, "Pneumonia Detection Through Cnn And Resnet-50," *Journal Of Baku Engineering University-Mathematics And Computer Science 2024*, vol. 8, no. 1, pp. 64–72, doi: 10.30546/09090.2024.110.212.

[26] A. Younis *et al.*, "Abnormal Brain Tumors Classification Using ResNet50 and Its Comprehensive Evaluation," *IEEE Access*, vol. 12, pp. 78843–78853, 2024, doi: 10.1109/ACCESS.2024.3403902.

[27] R. R. Ali *et al.*, "Learning Architecture for Brain Tumor Classification Based on Deep Convolutional Neural Network: Classic and ResNet50," *Diagnostics*, vol. 15, no. 5, Mar. 2025, doi: 10.3390/diagnostics15050624.

[28] A. Dede *et al.*, "Wavelet-Based Feature Extraction for Efficient High-Resolution Image Classification," *Engineering Reports*, vol. 7, no. 2, Feb. 2025, doi: 10.1002/eng2.70027.

[29] D. Hastari, S. Winanda, A. R. Pratama, N. Nurhaliza, and E. S. Ginting, "Application of Convolutional Neural Network ResNet-50 V2 on Image Classification of Rice Plant Disease," *Public Research Journal of Engineering, Data Technology and Computer Science*, vol. 1, no. 2, Feb. 2024, doi: 10.57152/predatecs.v1i2.865.

[30] N. Behar and M. Shrivastava, "ResNet50-Based Effective Model for Breast Cancer Classification Using Histopathology Images," *CMES - Computer Modeling in Engineering and Sciences*, vol. 130, no. 2, pp. 823–839, 2022, doi: 10.32604/cmes.2022.017030.

[31] A. Shabbir *et al.*, "Satellite and Scene Image Classification Based on Transfer Learning and Fine Tuning of ResNet50," *Math Probl Eng*, vol. 2021, 2021, doi: 10.1155/2021/5843816.