

Classification of Mango Varieties from Leaf Images Using ResNet-50 CNN Architecture

Neilsen Nicholas Komah^{1*}, Dedy Hermanto²

^{1,2}Multi Data Palembang University, Indonesia,

¹neilsennn@mhs.mdp.ac.id, ²dedy@mdp.ac.id



*Corresponding Author

Article History:

Submitted: 10-07-2025

Accepted: 20-07-2025

Published: 24-07-2025

Keywords:

Mango leaf classification;
ResNet-50; Convolutional Neural
Network; Image augmentation;
Hyperparameter tuning.

**Brilliance: Research of
Artificial Intelligence** is licensed
under a Creative Commons
Attribution-NonCommercial 4.0
International (CC BY-NC 4.0).

ABSTRACT

Early identification of mango (*Mangifera indica* L.) varieties is crucial for optimizing cultivation, as each variety possesses distinct characteristics and regional adaptability. However, the morphological similarities in leaf shape and texture especially among Harumanis, Erwin, Cokanan, Gedong Gincu, and Mahatir pose challenges for novice farmers and hobbyists. This study proposes a classification system using the Convolutional Neural Network (CNN) method with the ResNet-50 architecture to classify mango leaf varieties based on image data. A total of 5,000 images were collected and augmented from 1,250 original samples using a high-resolution camera under controlled indoor conditions. The dataset was split into training (80%), validation (10%), and testing (10%). Sixteen experimental configurations were evaluated using combinations of image resolutions (160×160 and 320×320 pixels), learning rates (0.01, 0.001), batch sizes (16, 32), and training epochs (50, 100). The best results were achieved using a 320×320 image size, learning rate of 0.001, batch size of 32, and 100 epochs, yielding a validation accuracy of 89.9%, precision of 89.87%, recall of 89.9%, and F1-score of 89.83%. These results confirm that high-resolution images and fine-tuned hyperparameters significantly enhance classification performance. The findings demonstrate the effectiveness of the ResNet-50 model for fine-grained classification in agriculture and support its future deployment in real-world environments for cultivar identification, quality control, and intelligent crop management.

INTRODUCTION

Mango (*Mangifera indica* L.) is one of the most popular and widely cultivated tropical fruits in the world, including in Indonesia. In addition to its sweet and refreshing taste, mango also has high economic value and makes a significant contribution to the agricultural sector. (Mardiah et al., 2024). This fruit is not only consumed fresh but is also processed into various derivative products such as juice, jam, candied mango, and others. Mango trees are known to grow easily in various tropical climate conditions and have a long productive lifespan, making them an attractive option for farmers.

Mango (*Mangifera indica* L.) is classified under the kingdom *Plantae*, division *Tracheophyta*, class *Magnoliopsida*, order *Sapindales*, and family *Anacardiaceae*. This species belongs to the genus *Mangifera* and is native to South Asia. The name *Mangifera indica* refers to a fruit-bearing plant originating from India. Globally, there are over 1,000 known mango varieties, which are generally categorized based on seed type into monoembryonic (single embryo) and polyembryonic (multiple embryos). Monoembryonic types are typically found in India, while polyembryonic types are more common in the Indochina region (Ali et al., 2025).

The mango tree is a seasonal fruit plant that originally came from India and later expanded to Southeast Asian regions, including Indonesia. Due to its extensive genetic variation, mango holds strong potential for further development. This genetic diversity is reflected in the wide range of fruit shapes, sizes, and colors found across different varieties (Yan et al., 2024).

Mangifera indica L. is an evergreen tree that can grow up to 10–45 meters tall, with a dome-shaped canopy and dense foliage. The leaves are arranged spirally, measuring about 25 cm in length and 8 cm in width, and are often reddish when young. The small flowers are reddish-white or yellowish-green and grow at the tips of branches, numbering around 3,000 per cluster. The fruit has a large seed, thick yellow flesh, and a yellowish skin when ripe (Jabar et al., 2024).

In recent years, public interest in fruit cultivation, particularly mango, has shown a significant upward trend. (Andriani et al., 2019). This is driven by the high market demand for mangoes, both locally and for export, as well as increasing public awareness of the economic value and long-term benefits of the plant. Mango is known as a crop that is relatively easy to cultivate in various tropical climate conditions and has the potential for high yields with proper care.

The large number of mango plant varieties often makes it difficult for beginner mango enthusiasts or prospective farmers who are still unfamiliar with the plants to distinguish between the types they are planting or purchasing sometimes not knowing until the tree bears fruit 3 to 5 years later. However, understanding the type of mango plant



from the beginning of cultivation is crucial for the development of mango farming in Indonesia. Each variety has different characteristics and levels of resistance to diseases in various regions of the country, so this knowledge can help in selecting the most suitable type for local environmental conditions.

Various types of mangoes commonly cultivated in the Palembang area include Harumanis, Erwin, Cokanan, Gedong Gincu, and Mahatir. One way to distinguish between these mango varieties is by observing the shape and texture of the mango tree leaves (Hidayat, 2022). Based on field data, the shape and texture of the leaves of Harumanis, Erwin, Cokanan, Gedong Gincu, and Mahatir mango varieties share many similarities, making them difficult to distinguish with the naked eye. As a result, it is very challenging for laypeople to classify mango varieties solely based on the leaves. The most feasible solution is to leverage artificial intelligence technology using deep learning models to assist farmers and beginner mango enthusiasts in identifying the mango varieties they are cultivating.

Convolutional Neural Network (CNN) is a specialized category within deep learning that is well-known for its high efficiency in object detection, image segmentation, and pattern recognition. Through this CNN method, researchers have empirically demonstrated strong capabilities in classifying plant varieties using images, as shown in the work of Ilyas Perlindungan and his colleagues (Perlindungan & Risnawati, 2020). In the study conducted, the application of a Deep CNN model to classify chili plant types based on their leaves achieved the highest detection accuracy of 80%. A comparable investigation was conducted by Arief Saputro and his team (Saputro et al., 2022), employing a Convolutional Neural Network approach with transfer learning through the VGG16 model to identify longan plant varieties using leaf image data. The study reported a top accuracy of 79% and a validation performance of 82%. Prior research has indicated that the ResNet-50 architecture tends to deliver superior accuracy compared to other transfer learning frameworks. For example, a study by (Martomanggolo, 2021) which classified white blood cells using the ResNet-50 architecture reported better accuracy compared to VGG-16, GoogLeNet, and AlexNet. Another study conducted by Bana Falahki and his colleagues also demonstrated the superior performance of ResNet-50 in image classification tasks, further reinforcing its effectiveness in handling complex visual features for accurate classification results (Falahki et al., 2022) focused on flower image classification using the ResNet-50 and AlexNet architectures. The results showed an accuracy of 87% for AlexNet and 96% for ResNet-50. This study utilized the RetinaNet model with ResNet as its backbone to detect seat belt usage in drivers. This research classified mango varieties using Learning Vector Quantization (LVQ) based on the texture of leaf bones. The system achieved relatively moderate accuracy due to the limited dataset (6 training, 15 testing images), with cluster analysis showing the lowest recognition score in the Golek mango type, attributed to its lower brightness compared to other varieties (Ardhana et al., 2022). This study used ResNet architecture to classify wheat leaf diseases (Septoria and Stripe Rust) with a dataset of 291 images. Using transfer learning, the model achieved 98% accuracy, validating that ResNet is highly effective for disease detection in plant images even with limited data (Ridhovan & Suharso, 2022). This study applied ResNet-50 for binary image classification to detect pornographic content using the NPDI dataset. The experiment focused on investigating the impact of different epoch configurations (20–100 epochs) on classification accuracy. The best performance was achieved at 60 epochs, with an accuracy of 91.03%, indicating that an appropriate number of training iterations significantly improves model performance on sensitive image classification tasks (Faiz Nashrullah et al., 2020). This study classified three types of mangoes (Arumanis, Golek, and Manalagi) Utilizing the K-Nearest Neighbor (K-NN) algorithm, the classification was performed by analyzing leaf morphology and surface patterns. Feature extraction included compactness and circularity for shape, and energy and contrast from the co-occurrence matrix for texture. With a dataset of 90 images, the best classification accuracy reached 73.33% at K = 10, 12, and 15. The findings confirmed that combining shape and texture features improves classification effectiveness, despite challenges in distinguishing visually similar leaf types (Triyono et al., 2021) This research used YOLOv8 with transfer learning to classify organic and inorganic waste images under various image noise conditions (normal, blur, darkness, low resolution, motion blur). With 1178 images from Roboflow, the model achieved its best performance on normal images with F1-score of 0.99, while still maintaining high accuracy under noisy conditions. The study highlights YOLOv8's robustness for real-time waste detection systems (Prasetyo & Pratiwi, 2025).

Based on the literature review conducted on various cases and existing challenges, the author proposes the development of a mango plant variety detection system using leaf images by applying the CNN method with the ResNet-50 architecture.

LITERATURE REVIEW

The application of deep learning, particularly Convolutional Neural Networks (CNN), in plant classification has grown rapidly in recent years due to its ability to automatically extract spatial features from image data. Several studies have successfully employed CNN architectures for identifying plant species based on leaf morphology, demonstrating notable accuracy and efficiency compared to traditional image processing methods.

(Perlindungan & Risnawati, 2020) implemented a deep CNN model to classify chili plant varieties using leaf images and achieved an accuracy of 80%. Similarly, (Saputro et al., 2022) applied transfer learning using the VGG16 model for classifying longan plant varieties based on leaf features, obtaining a validation accuracy of 82%. These

studies confirm the potential of deep CNNs in capturing morphological patterns for plant identification, though the model performance still depends heavily on the dataset and feature clarity.

Among CNN architectures, ResNet-50 has emerged as a robust and reliable option due to its deep layers and residual connections, which help avoid vanishing gradient problems. (Martomanggolo, 2021) demonstrated that ResNet-50 outperformed other architectures like VGG16, GoogLeNet, and AlexNet in classifying white blood cells, indicating its strength in handling complex visual tasks. (Falakhi et al., 2022) further confirmed its superiority in flower classification tasks, achieving up to 96% accuracy.

In the context of agricultural image classification, ResNet-50 has been used in various tasks. (Ridhovan & Suharto, 2022) utilized it for detecting wheat leaf diseases, reaching 98% accuracy even with a limited dataset. A study (Faiz Nashrullah et al., 2020) applied ResNet-50 for binary image classification on sensitive datasets, also achieving high performance with careful tuning of training epochs. These works collectively highlight the effectiveness of ResNet-50 in small-to-medium scale image classification problems involving natural objects.

However, in the specific domain of mango plant classification, existing studies often face limitations in terms of dataset diversity and resolution. (Ardhana et al., 2022) used Learning Vector Quantization (LVQ) based on leaf texture and achieved moderate results due to small sample sizes and low feature clarity. Likewise, (Triyono et al., 2021) employed K-Nearest Neighbors (KNN) with morphological and texture features, but only reached 73.33% accuracy, showing the difficulty of distinguishing mango varieties with traditional methods.

These studies underline a gap in current research: while CNNs have been effective for various plant species, there is still limited work focusing on fine-grained classification of mango varieties using high-resolution image datasets and deep architectures such as ResNet-50. This gap motivates the present study to explore the use of ResNet-50 for mango leaf variety classification, with emphasis on resolution impact and hyperparameter optimization.

METHOD

The research followed a systematic set of procedures, illustrated in the flowchart shown in Figure 1. The initial stage involved an in-depth review of existing literature to examine how convolutional neural networks (CNN) have been applied in classifying plant types from leaf imagery, with a particular emphasis on mango leaves.

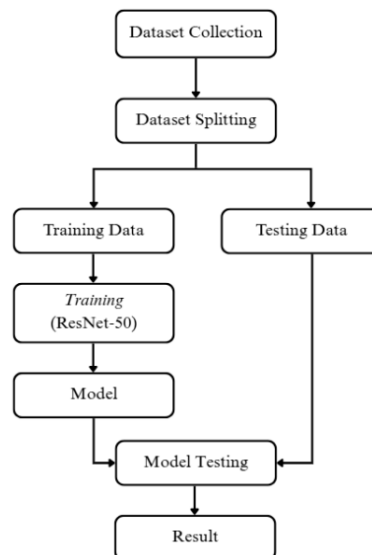


Fig. 1 Research Methodology Flowchart

The dataset was constructed by capturing leaf images of five mango varieties: Harumanis, Erwin, Cokanan, Gedong Gincu, and Mahatir. Each variety consisted of 250 leaf images, resulting in a total of 1,250 raw images prior to the augmentation process. These images were obtained from 50 individual leaves per variety, with each leaf photographed from both sides. To enrich the dataset, rotation and flip transformations were applied, generating five distinct images per leaf.

Image acquisition was conducted indoors, using a white background and controlled lighting to minimize shadows and ensure image consistency. All photos were taken from a top-down (top view) perspective to emphasize the morphological characteristics of the leaves. The imaging device used was an iPhone 14 Pro, with the camera positioned approximately 15 cm above the leaf surface. An example of the image capture setup is illustrated in Figure 2.

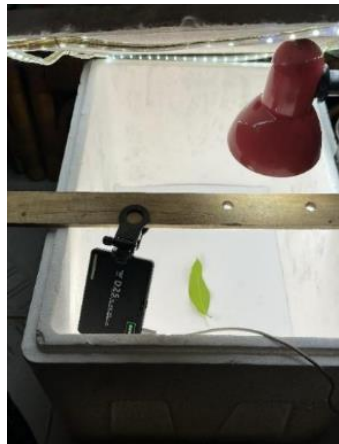


Fig. 2 Dataset Acquisition Process

Once the initial dataset was assembled, data augmentation techniques were applied to expand the sample size and enhance the model's ability to generalize. Each category was increased to 1,000 images, culminating in a dataset of 5,000 images representing five distinct mango leaf types. Augmentation included randomly rotating images between -30° and $+30^\circ$, along with horizontal and vertical flips. Following augmentation, the dataset was divided into training (80%), validation (10%), and testing (10%) sets. This division aimed to preserve class distribution and ensure consistent evaluation throughout the model development process.

The study adopted ResNet-50 as the model architecture, a deep CNN that utilizes residual connections to address vanishing gradient challenges and improve training efficiency in deep-layered networks. The model was built using TensorFlow and Keras, which offer extensive tools for constructing, training, and evaluating deep learning models. To test model performance across different scenarios, sixteen experimental setups were designed by systematically adjusting four primary hyperparameters: learning rates (0.01 and 0.001), batch sizes (16 and 32), image dimensions (160×160 and 320×320 pixels), and number of epochs (50 and 100). The model compilation employed the Adam optimizer due to its adaptive learning mechanism and reliable convergence properties. The categorical cross-entropy loss function was used, as it is ideal for handling multi-class classification problems such as distinguishing mango leaf types.

Accuracy serves as a key performance indicator in classification problems, defined as the ratio of correct predictions to the total number of predictions made by the model. It offers a broad assessment of model effectiveness and is computed as shown in equation (1). Here, True Positives (TP) refer to correctly identified positive cases, True Negatives (TN) represent accurately predicted negative cases, False Positives (FP) are negative samples incorrectly labeled as positive, and False Negatives (FN) are positive samples misclassified as negative. While higher accuracy suggests stronger overall predictive ability, it is important to interpret this metric alongside others—especially when dealing with class imbalance or multiple categories.

$$accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

Precision represents the ratio of correctly predicted positive outcomes to the total instances that the model classified as positive. It indicates how well the model avoids false positives and is defined in equation (2). On the other hand, recall assesses the model's capability to detect all actual positive cases within the dataset, indicating its sensitivity to identifying the positive class, as outlined in equation (3). These two metrics are essential for understanding the balance between missing true positives and generating excessive false alarms, particularly in multi-class classification tasks or when dealing with imbalanced datasets.

$$precision = \frac{TP}{TP+FP} \quad (2)$$

$$recall = \frac{TP}{TP+FN} \quad (3)$$

The F1-score provides an integrated assessment by combining precision and recall into a single metric through their harmonic mean, as illustrated in equation (4). It offers a balanced perspective by taking into account both false positives and false negatives, making it particularly effective for scenarios involving class imbalance or when precision–recall trade-offs are critical. A higher F1-score implies that the model performs well in terms of both precision and recall, indicating a robust and reliable prediction capability.

$$F1\ score = 2 \times \frac{precision \times recall}{precision + recall} \quad (4)$$

RESULT

This section provides a comprehensive analysis of the experimental results with the objective of identifying the most effective hyperparameter configuration for the ResNet-50 architecture applied to the classification of mango leaf varieties. To achieve this, a total of eight experimental scenarios were systematically tested by varying several critical hyperparameters, including batch size, number of training epochs, learning rate, and input image resolution. These variations were carefully designed to observe their influence on model performance, stability, and generalization ability across different training conditions. The experiments were conducted using a dataset comprising 5,000 mango leaf images, with 1,000 images allocated for each of the five different mango varieties: Harumanis, Erwin, Cokanan, Gedong Gincu, and Mahatir. This balanced class distribution ensures fair evaluation and minimizes bias during the training and testing processes. The detailed class composition and distribution can be found in Table 1. To support open science and encourage further research in the field of plant classification using deep learning, the complete dataset has been made publicly available. It can be accessed and downloaded freely via the following DOI link: <https://doi.org/10.5281/zenodo.15708979>. The open availability of the dataset ensures transparency, allows for reproducibility of results, and provides a valuable resource for researchers aiming to benchmark or extend this study.

Table 1. Details of the Dataset Used

Number	Mango Variety	Count	Example Image
1	Harumanis	1000	
2	Erwin	1000	
3	Cokanan	1000	
4	Gedong Gincu	1000	
5	Mahatir	1000	

Table 2. ResNet-50 Test Results (Image Size 160×160)

Number	Learning Rate	Batch Size	Epoch	Validation Accuracy	Precision	Recall	F1-Score
1	0.01	16	50	0.823	0.8201	0.823	0.8195
2	0.01	16	100	0.838	0.8350	0.838	0.8352
3	0.01	32	50	0.840	0.8375	0.840	0.8368
4	0.01	32	100	0.852	0.8490	0.852	0.8493
5	0.001	16	50	0.847	0.8432	0.847	0.8448
6	0.001	16	100	0.867	0.8641	0.867	0.8645
7	0.001	32	50	0.869	0.8662	0.869	0.8667
8	0.001	32	100	0.882	0.8800	0.882	0.8802

Table 2 outlines the performance outcomes of the ResNet-50 model applied to mango leaf classification, utilizing input images sized at 160×160 pixels. The experiments explored different combinations of hyperparameters, including learning rates (0.01 and 0.001), batch sizes (16 and 32), and training epochs (50 and 100). Model performance was assessed based on four primary evaluation metrics: validation accuracy, precision, recall, and F1-score.

The results indicate a consistent improvement in model performance when the number of epochs is increased from 50 to 100, regardless of the learning rate or batch size. For example, with a learning rate of 0.001 and batch size of 32, the validation accuracy improved from 0.869 (at 50 epochs) to 0.882 (at 100 epochs). Similarly, the F1-score rose from 0.8667 to 0.8802, indicating better balance between precision and recall.

Furthermore, models trained with a lower learning rate (0.001) outperformed those with a higher learning rate (0.01) across all configurations. This suggests that a smaller learning rate allows for more stable and refined weight updates, which is especially beneficial for a deep architecture like ResNet-50.

In terms of batch size, larger batches (i.e., batch size of 32) generally produced higher validation scores than smaller ones (batch size of 16), particularly when combined with 100 training epochs and a low learning rate.

In conclusion, the best-performing configuration for image size 160×160 was achieved using a learning rate of 0.001, batch size of 32, and 100 epochs, yielding the highest validation accuracy (0.882) and F1-score (0.8802). This configuration demonstrates the importance of deeper training, smaller learning rate, and moderate batch size in optimizing model performance for this dataset.

Table 3. ResNet-50 Test Results (Image Size 320×320)

Number	Learning Rate	Batch Size	Epoch	Validation Accuracy	Precision	Recall	F1-Score
1	0.01	16	50	0.810	0.8087	0.810	0.8062
2	0.01	16	100	0.829	0.8260	0.829	0.8255
3	0.01	32	50	0.845	0.8421	0.845	0.8423
4	0.01	32	100	0.861	0.8585	0.861	0.8587
5	0.001	16	50	0.855	0.8515	0.855	0.8522
6	0.001	16	100	0.873	0.8700	0.873	0.8705
7	0.001	32	50	0.878	0.8751	0.878	0.8755
8	0.001	32	100	0.899	0.8987	0.899	0.8983

Table 3 displays the performance outcomes of the ResNet-50 model when applied to a mango leaf classification task using an input image resolution of 320×320 pixels. The evaluation was conducted by varying the learning rate (0.01 and 0.001), batch size (16 and 32), and training epochs (50 and 100). The model performance was assessed using four evaluation metrics: Validation Accuracy, Precision, Recall, and F1-Score.

A consistent trend observed in the results is that increasing the number of training epochs from 50 to 100 tends to improve overall performance across all metrics. For instance, with a learning rate of 0.001 and batch size 32, increasing the training duration from 50 to 100 epochs resulted in an increase in validation accuracy from 0.878 to 0.899, and F1-Score from 0.8755 to 0.8983. A similar pattern was observed in the configuration with learning rate 0.01 and batch size 32, where accuracy increased from 0.845 (50 epochs) to 0.861 (100 epochs), and F1-score from 0.8423 to 0.8587.

Furthermore, using a lower learning rate (0.001) consistently resulted in better performance than 0.01 in all cases. This aligns with general deep learning practices, where smaller learning rates allow the model to converge more gradually and accurately, especially in deeper networks such as ResNet-50.

Additionally, increasing the batch size from 16 to 32 also contributed positively to performance, especially when combined with longer training (100 epochs). Among all the tested configurations, the best performance was achieved with a learning rate of 0.001, batch size of 32, and 100 training epochs. This configuration yielded the highest values in all evaluation metrics, with a validation accuracy of 0.899, precision of 0.8987, recall of 0.899, and F1-Score of 0.8983.

To conclude, the experimental results indicate that the ResNet-50 architecture performed more effectively when trained on higher-resolution input images (320×320 pixels) compared to lower-resolution ones (160×160 pixels). The most effective configuration—a learning rate of 0.001, batch size of 32, and 100 training epochs—consistently delivered the best validation accuracy and F1-score across both image sizes. Nevertheless, the 320×320 resolution produced the overall best outcomes, achieving a validation accuracy of 89.9% and an F1-score of 89.83%, underscoring the value of high-resolution imagery and carefully optimized hyperparameters in enhancing classification accuracy for fine-grained plant identification tasks.

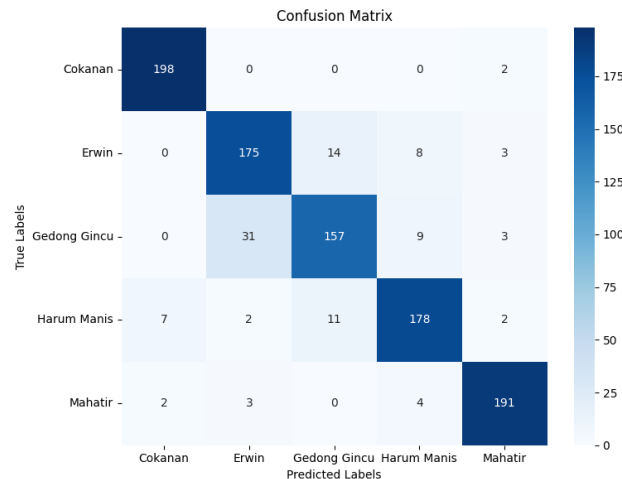


Fig 3. The confusion matrix for Experiment #8, which utilized an input image resolution of 320×320 pixels

Figure 3 presents the confusion matrix obtained from Experiment #8, which utilized the ResNet-50 architecture with an input image resolution of 320×320 pixels. This matrix illustrates the distribution of the model's predictions across the five mango leaf varieties: Cokanan, Erwin, Gedong Gincu, Harum Manis, and Mahatir. The strong diagonal dominance observed in the matrix indicates that the model was generally effective in correctly classifying the majority of samples.

The Cokanan variety achieved the highest classification performance, with 198 out of 200 samples correctly identified and only 2 misclassified as Mahatir. This suggests that the morphological characteristics of Cokanan leaves such as shape, venation patterns, or texture are distinctive enough to be learned reliably by the model.

The Erwin class had 175 correctly classified samples, while 14 were misclassified as Gedong Gincu, 8 as Harum Manis, and 3 as Mahatir. This level of confusion suggests a visual similarity between Erwin and Gedong Gincu leaves, which may share overlapping features that the model struggled to distinguish.

The Gedong Gincu class posed the greatest challenge, with only 157 correct predictions. A total of 31 samples were misclassified as Erwin and 9 others into different categories. This indicates that Gedong Gincu leaves may lack distinctive visual features or have significant overlap with other classes, making them more difficult for the model to separate accurately.

The Harum Manis class resulted in 178 correct classifications, with most misclassifications occurring as Cokanan (7 samples) and Gedong Gincu (11 samples). While the model performed well overall, the errors imply that Harum Manis shares subtle similarities in leaf shape or tone with other classes.

The Mahatir class also performed strongly, with 191 correct classifications. The remaining 9 misclassified samples were distributed across Harum Manis, Cokanan, and Erwin, indicating minimal confusion and a high degree of reliability for this variety.

In summary, the confusion matrix confirms that the ResNet-50 model is highly capable of distinguishing most mango leaf varieties, particularly Cokanan and Mahatir. However, the classification of Gedong Gincu remains challenging due to its visual resemblance to Erwin. These findings emphasize the need for enhanced dataset diversity and further refinement in feature extraction to improve classification accuracy in real-world agricultural scenarios.

DISCUSSION

This section discusses the analysis of experimental findings involving the ResNet-50 model tested with two distinct image resolutions: 160×160 and 320×320 pixels. The experiments aimed to assess how input image size and various hyperparameter settings such as learning rate, batch size, and number of training epochs influence the model's performance in classifying five mango leaf cultivars: Cokanan, Erwin, Gedong Gincu, Harum Manis, and Mahatir.

From the 160×160 resolution experiments, the best configuration was achieved using a learning rate of 0.001, batch size of 32, and 100 training epochs, which yielded a validation accuracy of 0.882, precision of 0.880, recall of

0.882, and an F1-score of 0.8802. The results show a clear improvement when the model is trained with more epochs and a slightly larger batch size, indicating greater stability and better convergence behavior. Conversely, configurations with lower epochs (50) or higher learning rates (0.01) generally resulted in lower performance metrics, highlighting the sensitivity of the model to these parameters.

In comparison, the 320×320 resolution setup demonstrated superior performance overall. The best configuration was also achieved with a learning rate of 0.001, batch size of 32, and 100 epochs, matching the settings of the best 160×160 model. However, the 320×320 model significantly outperformed the 160×160 counterpart, reaching a validation accuracy of 0.899, precision of 0.8987, recall of 0.899, and F1-score of 0.8983. This suggests that higher-resolution images contain richer spatial information, allowing the deep ResNet-50 model to extract more meaningful and discriminative features, particularly helpful in fine-grained classification where leaf morphology plays a critical role.

The performance gain from 160×160 to 320×320 resolutions under identical hyperparameter conditions emphasizes the importance of image quality and detail in classification tasks involving subtle visual differences. Furthermore, the consistent performance improvements observed across configurations with increased epochs reinforce the importance of adequate training duration, particularly when coupled with a stable optimizer and well-tuned learning rate.

To verify the reported F1-score for the best configuration using Equation (4)

$$F1\ score = 2 \times \frac{precision \times recall}{precision + recall}$$

$$F1\ score = 2 \times \frac{0.8987 \times 0.899}{0.8987 + 0.899} = 0.8983$$

This manual verification supports the accuracy and dependability of the reported F1-score, indicating that the model effectively balanced the reduction of false positives with the successful identification of true positives.

The performance gap between the two resolutions under identical hyperparameters highlights the significance of spatial detail in deep learning-based classification, especially in domains like agriculture, where fine-grained visual distinctions are critical. Additionally, the consistent performance boost observed with extended training epochs confirms that model depth must be matched with sufficient training duration to unlock the full potential of a deep architecture like ResNet-50.

In summary, the 320×320 resolution with learning rate 0.001, batch size 32, and 100 epochs emerged as the most effective setup for this classification task, delivering high accuracy and strong generalization. These findings provide a solid foundation for future implementations in real-world agricultural systems, and demonstrate that both image quality and hyperparameter configuration play pivotal roles in CNN-based plant identification workflows.

CONCLUSION

Based on the experimental results, the effectiveness of the ResNet-50 convolutional neural network (CNN) architecture was successfully demonstrated in the classification of five mango leaf varieties, namely Cokanan, Erwin, Gedong Gincu, Harum Manis, and Mahatir. Sixteen experimental configurations were explored, each combining different settings of key hyperparameters such as learning rate, batch size, input image resolution, and the number of training epochs. The primary objective was to identify the optimal parameter configuration that maximized classification accuracy while maintaining stable and generalizable model performance.

Among the two input resolutions evaluated, the model trained on 320×320 pixel images consistently achieved better results than the one trained on 160×160 pixel inputs. This outcome underscores the significance of spatial resolution in detailed classification tasks, especially when leaf morphology is critical. The best performance was obtained using a configuration that included a learning rate of 0.001, batch size of 32, 100 training epochs, and 320×320 input resolution, resulting in a validation accuracy of 89.9%, precision of 89.87%, recall of 89.9%, and an F1-score of 89.83%. These performance metrics were also validated through manual calculation using the F1-score equation, affirming the model's robust and well-balanced classification effectiveness.

The results emphasize the role of proper hyperparameter tuning and the utility of deeper CNN architectures like ResNet-50 in agricultural classification tasks. Furthermore, the Adam optimizer contributed significantly to the model's convergence speed and stability, reinforcing its effectiveness for medium-scale image datasets. The successful identification of mango cultivars with high precision and recall also suggests the feasibility of deploying such models in real-world agricultural environments to support tasks like variety tracking, quality control, and supply chain management.

While the results are promising, they are based on a dataset captured under controlled indoor conditions. Future work should investigate the model's robustness in real-world environments by expanding the dataset with images taken under natural lighting, varied backgrounds, and diverse leaf conditions. Additionally, deployment of the trained model



on mobile or edge devices could enhance its practical utility for on-site mango cultivar identification and decision-making in agricultural applications.

In conclusion, the study highlights that deep learning approaches, particularly ResNet-50 with optimized hyperparameters and adequate image resolution, offer a reliable and scalable solution for fine-grained plant classification challenges. The findings also provide a strong foundation for future research into intelligent agricultural systems, where CNN-based models can assist not only in plant variety recognition but also in disease detection, growth stage monitoring, and automated crop management. Expanding the model's adaptability through transfer learning, real-time inference, and integration with Internet of Things (IoT) platforms could significantly enhance its impact in the field of precision agriculture.

REFERENCES

- Ali, G. S., Eltaher, S., Li, J., Freeman, B., & Singh, S. (2025). GWAS identifies a polyembryony locus in mango: development of KASP and PACE markers for marker-assisted breeding. *Frontiers in Plant Science*, 16(January), 1–15. <https://doi.org/10.3389/fpls.2025.1508027>
- Andriani, R., Rasmikayati, E., Mukti, G. W., & Fatimah, S. (2019). Faktor-faktor yang Mempengaruhi Keputusan Petani Mangga dalam Pemilihan Pasar di Kabupaten Indramayu. *Jurnal Penyuluhan*, 15(2), 286–298. <https://doi.org/10.25015/penyuluhan.v15i2.27736>
- Ardhana, V. Y. P., Saputra, J., & Afriansyah, M. (2022). Klasifikasi Jenis Mangga Berdasarkan Tekstur Tulang Daun Menggunakan Metode Learning Vector Quantization (LVQ). *Journal of Computer System and Informatics (JoSYC)*, 4(1), 220–228. <https://doi.org/10.47065/josyc.v4i1.2420>
- Faiz Nashrullah, Suryo Adhi Wibowo, & Gelar Budiman. (2020). The Investigation of Epoch Parameters in ResNet-50 Architecture for Pornographic Classification. *Journal of Computer, Electronic, and Telecommunication*, 1(1), 1–8. <https://doi.org/10.52435/complete.v1i1.51>
- Falakhi, B., Achmal, E. F., Rizaldi, M., Athallah, R. R. R., & Yudistira, N. (2022). Perbandingan Model AlexNet dan ResNet dalam Klasifikasi Citra Bunga Memanfaatkan Transfer Learning. *Jurnal Ilmu Komputer dan Agri-Informatika*, 9(1), 70–78. <https://doi.org/10.29244/jika.9.1.70-78>
- Hidayat, D. (2022). Klasifikasi Jenis Mangga Berdasarkan Bentuk Dan Tekstur Daun Menggunakan Metode Convolutio Nalneural Network(Cnn) Classification of Types of Mango Based on Leave Shape and Texture Using Convolutio Nalneural Network(Cnn) Method. *Journal of Information Technology and Computer Science (INTECOMS)*, 5(1), 98–103.
- Jabar, M. A., Nadifa, J. A., & Sulistiyowati, M. (2024). Comprehensive Study of the Morphology and Anatomy of Mango (*Mangifera indica*) as a Differentiator from Other Species: A Literature Review Kajian Komprehensif Morfologi dan Anatomi Mangga (*Mangifera indica*) Sebagai Pembeda dari Spesies yang Lain: Sebuah Literature Review. *Jurnal Serambi Biologi*, 9(1), 138–151.
- Mardiah, A. H., Wulandari, Y. S., & Syahputra, F. (2024). Analisis Faktor-Faktor yang Memengaruhi Pendapatan Petani Mangga (*Mangifera indica* L .) di Desa Sumberjaya Kecamatan Tempuran Kabupaten Karawang. 12(2), 321–328.
- Martomanggolo, D. (2021). Perbandingan Convolutional Neural Network pada Transfer Learning Method untuk Mengklasifikasikan Sel Darah Putih. *Ultimatics : Jurnal Teknik Informatika*, 13(1), 51.
- Perlindungan, I., & Risnawati. (2020). Pengenalan Tanaman Cabai Dengan Teknik Klasifikasi Menggunakan Metode CNN. *Seminar Nasional Mahasiswa ilmu Komputer dan Aplikasinya (SENAMIKA)*, 15–22.
- Prasetio, B., & Pratiwi, N. (2025). Deteksi sampah organik dan anorganik menggunakan model yolov8. 10(1), 494–506.
- Ridhovan, A., & Suharno, A. (2022). Penerapan Metode Residual Network (Resnet) Dalam Klasifikasi Penyakit Pada Daun Gandum. *JIPi (Jurnal Ilmiah Penelitian dan Pembelajaran Informatika)*, 7(1), 58–65. <https://doi.org/10.29100/jipi.v7i1.2410>
- Saputro, A., Mu'min, S., Moch. Lutfi, & Putri, H. (2022). Deep Transfer Learning Dengan Model Arsitektur Vgg16 Untuk Klasifikasi Jenis Varietas Tanaman Lengkeng Berdasarkan Citra Daun. *JATI (Jurnal Mahasiswa Teknik Informatika)*, 6(2), 609–614. <https://doi.org/10.36040/jati.v6i2.5456>
- Triyono, A., Trianto, R. B., & Arum, D. M. P. (2021). Penerapan Least Squares Support Vector Machines (LSSVM) dalam Peramalan Indonesia Composite Index. *Jurnal Informatika Universitas Pamulang*, 6(1), 210. <https://doi.org/10.32493/informatika.v6i1.10237>
- Yan, J., Zheng, B., Wang, S., Xu, W., Qian, M., Ma, X., & Wu, H. (2024). Genetic Diversity and Fingerprinting of 231 Mango Germplasm Using Genome SSR Markers. *International Journal of Molecular Sciences*, 25(24). <https://doi.org/10.3390/ijms252413625>