Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control
Journal homepage: http://kinetik.umm.ac.id
ISSN: 2503-2267
Vol. 9, No. 2, May 2024, Pp.149-158

Tomato leaf diseases classification using convolutional neural networks with transfer learning Resnet-50

Muslih*[1], Andi Danang Krismawan[1]
University of Dian Nuswantoro, Indonesia[1]

Article Info

Keywords:
Tomato Leaf Disease, Image Classification, CNN, Resnet-50, Confusion Matrix

Article history:
Received: December 27, 2023
Accepted: April 17, 2024
Published: May 31, 2024

Cite:
Muslih and A. D. Krismawan, "Tomato Leaf Diseases Classification using Convolutional Neural Networks with Transfer Learning Resnet-50", KINETIK, vol. 9, no. 2, May 2024. Retrieved from https://kinetik.umm.ac.id/index.php/kinetik/article/view/1939

*Corresponding author.
Muslih
E-mail address:
muslih@dsn.dinus.ac.id

Abstract

This research delves into the critical domain of Tomato Leaf Disease classification using advanced machine learning techniques. Specifically, a comparative evaluation was conducted between a Base CNN model devoid of ResNet-50 integration and a Proposed Method harnessing the capabilities of ResNet-50. The results elucidated a notable enhancement in performance metrics when leveraging ResNet-50, with the Proposed Method consistently achieving exceptional accuracy scores of 99.96%, 99.98%, and 99.96% across data splits of 90:10, 80:20, and 70:30, respectively. Furthermore, the ResNet-50 integration significantly augmented key metrics, including recall, precision, and F1-Score, thereby accentuating its pivotal role in enhancing sensitivity and positive predictive value for tomato leaf disease classification. As for prospective research trajectories, this study highlights potential avenues for refinement, encompassing the exploration of ensemble techniques amalgamating diverse architectural frameworks, advanced data augmentation methodologies, and broader disease classification scopes. Collectively, this research underscores the transformative potential of ResNet-50 in agricultural diagnostics, advocating for continued exploration and innovation to fortify global food security and sustainable farming practices. Future research could explore ensemble techniques, advanced data augmentation, broader disease classification scopes, and interdisciplinary collaborations to develop comprehensive diagnostic tools for sustainable farming practices and global food security.

1. Introduction

Image classification is a foundational task within the realm of computer vision, wherein the objective is to assign a predefined label or category to an input image based on its visual content [1]–[3]. This process leverages advanced machine learning algorithms, particularly convolutional neural networks (CNN), to extract intricate features from the images and subsequently make informed decisions about their classification [4], [5]. The significance of image classification extends across numerous domains, ranging from medical diagnostics and autonomous vehicles to agricultural monitoring and surveillance systems. The focal point of investigation revolves around tomato leaf diseases, serving as the primary subject matter for classification purposes [6], [7]. Leveraging advancements in machine learning, particularly CNN, the study endeavors to accurately identify and categorize various ailments affecting tomato leaves based on their visual manifestations. Recognizing the significance of timely disease detection in agricultural contexts, the research aims to develop a robust classification model that can aid farmers and stakeholders in early diagnosis, thereby facilitating prompt interventions and ensuring optimal crop health and yield [8].

CNN is a pivotal deep learning architecture renowned for its proficiency in image recognition tasks, particularly when confronted with complex visual datasets such as disease-infected tomato leaves [5], [9]. In the context of this study, the utilization of the ResNet-50 model through transfer learning emerges as a strategic approach to harness the pre-trained knowledge embedded within this sophisticated neural network [10]–[12]. By leveraging the foundational features extracted by ResNet-50 from extensive datasets, the research endeavors to optimize the classification process, enabling accurate and efficient identification of various tomato leaf diseases. This methodological choice not only underscores the potential of transfer learning in enhancing classification accuracy but also underscores its practical implications in agricultural contexts, offering farmers and stakeholders a valuable tool for timely disease management and ensuring sustainable crop productivity [13].

Numerous researchers have adopted Convolutional Neural Networks (CNNs) as the primary tool for classifying images of tomato leaf diseases, each employing their innovative approaches. Maeda et al. [14] represent a comprehensive study that delves into the critical issue of tomato plant diseases, emphasizing the imperative need for timely and accurate diagnoses to safeguard crop quality. Recognizing the transformative potential of deep learning techniques, particularly convolutional neural networks (CNNs), the research meticulously evaluates several state-of-the-art architectures: AlexNet, GoogleNet, Inception V3, ResNet 18, and ResNet 50. The experimentation leverages a dataset encapsulating nine distinct classes of tomato diseases, complemented by a healthy class sourced from PlantVillage. Through rigorous multiclass statistical analyses, encompassing metrics such as accuracy, precision, sensitivity, specificity, F-Score, area under the curve (AUC), and the receiving operating characteristic (ROC) curve, the efficacy of each model is critically assessed. Remarkably, the findings elucidate the unparalleled performance of the GoogleNet technique, culminating in an astounding 99.72% AUC and 99.12% sensitivity. Paul er al. [15] represent a pivotal contribution in the domain of agricultural technology, emphasizing the paramount importance of early diagnosis and treatment of tomato leaf diseases to bolster a plant's production volume, efficiency, and quality. Their research underscores the critical repercussions of misdiagnosis by farmers, which can inadvertently lead to suboptimal treatment strategies detrimental to both tomato plants and the broader agroecosystem. Addressing this challenge head-on, Paul et al. proposed a lightweight custom convolutional neural network (CNN) model and judiciously employed transfer learning (TL) techniques using VGG-16 and VGG-19 architectures for disease classification. In their comprehensive analysis encompassing eleven distinct disease classes, inclusive of a healthy category, they meticulously conducted an ablation study to discern the most efficacious parameters for their custom model. Through rigorous evaluation metrics, they adeptly juxtaposed the performance of their proposed model against TL-based counterparts. Remarkably, the model, fortified by adept data augmentation techniques, culminated in an exemplary accuracy and recall rate of 95.00%. Conclusively, leveraging their findings, Paul et al. ingeniously fashioned an end-to-end (E2E) system accessible via web and Android platforms, thereby equipping tomato cultivators with a cutting-edge tool that achieves a commendable disease classification accuracy of 95%. Chen et al. [16] represent a groundbreaking effort in leveraging deep learning for agricultural automation, particularly focusing on the pressing challenges faced by farmers worldwide in managing tomato leaf diseases caused by various pathogens such as viruses, fungi, and insects. Recognizing the transformative potential of deep learning, the authors implemented a modified AlexNet architecture-based CNN model specifically tailored for the Android platform. Their dataset encompassed 18,345 training samples and 4,585 testing samples, each image segmented into ten distinct labels corresponding to tomato leaf diseases, with dimensions of 64 × 64 RGB pixels. Through meticulous optimization, the model was fine-tuned using the Adam optimizer with a learning rate set at 0.0005, spanning 75 epochs, and a batch size of 128, complemented by an uncompromising cross-entropy loss function. Impressively, the resultant model exhibited an exemplary accuracy rate averaging 98%. Furthermore, the precision rate stood at 0.98, the recall value peaked at 0.99, and the F1-score was an impressive 0.98, all culminating in a minimal loss of 0.1331. Such outcomes underscore the model's efficacy, yielding classification results characterized by their robustness and precision. Sembiring et al. [17] represents a significant contribution in the realm of plant disease detection, specifically targeting tomato plants based on leaf images. Their primary objective was to ascertain a streamlined CNN architecture that strikes a harmonious balance between computational simplicity and accuracy. This pursuit was rooted in the ambition to cultivate a standalone system model tailored for field applications, especially in settings constrained by budgetary limitations and scarce resources. The architecture they proposed was meticulously derived from a baseline CNN structure, tailored to categorize 10 distinct classes of tomato leaves, encompassing one healthy category and nine disease-afflicted classes sourced from the PlantVillage dataset. To benchmark their proposed model's efficacy, Sembiring et al. juxtaposed its performance against several established CNN architectures prevalent in the literature, including VGG Net, ShuffleNet, and SqueezeNet. Impressively, their findings elucidated that the proposed architecture not only rivaled the accuracy benchmarks set by its counterparts but also exhibited superior efficiency. Specifically, the proposed model attained an exemplary accuracy of 97.15%, underscoring its efficacy and potential for real-world applications.

The research objective underscores the utilization of Convolutional Neural Networks (CNN), specifically employing transfer learning with the ResNet-50 architecture. For this study, images are standardized to a dimensionality of 227 x 227 x 3 pixels, optimizing for the intricacies of the dataset at hand. The dataset encompasses a comprehensive collection of 32,535 images, meticulously curated to encapsulate the nuances of 10 distinct classes. By harnessing the power of transfer learning, the research aims to leverage the pre-trained features embedded within ResNet-50, thereby enhancing the model's efficiency and accuracy in classifying the myriad complexities associated with the dataset's 11 categories. This strategic approach not only facilitates streamlined model training but also ensures robust performance, catering to the multifaceted requirements of the classification task at hand.

2. Research Method

In the proposed method, the research embarks on a systematic approach to elucidate the intricacies of image classification. Initially, the study meticulously curates and preprocesses datasets, ensuring their quality and relevance for subsequent analyses. A pivotal step in this phase involves resizing the data, transitioning from random dimensions to a standardized format of 227 x 227 x 3 pixels, thereby facilitating uniformity across the dataset. Subsequent to resizing, the data undergoes contrast and quality enhancement techniques to augment its clarity and discriminatory features. Following these preprocessing steps, the dataset is judiciously split into distinct training and testing subsets, ensuring the integrity and generalizability of the model. Delving into the training phase, the research harnesses the prowess of transfer learning, specifically leveraging the ResNet-50 architecture, to capitalize on pre-existing knowledge and expedite the model's convergence. Two pivotal outcomes emerge from this endeavor: one elucidating the model's performance without the aid of transfer learning and another accentuating the augmented capabilities conferred by transfer learning techniques. To quantify and validate the model's efficacy, a comprehensive confusion matrix evaluation is conducted, culminating in the classification phase where the model's prowess in discerning intricate patterns and categorizing images is rigorously assessed. Based on proposed method, it can be seen in Figure 1.

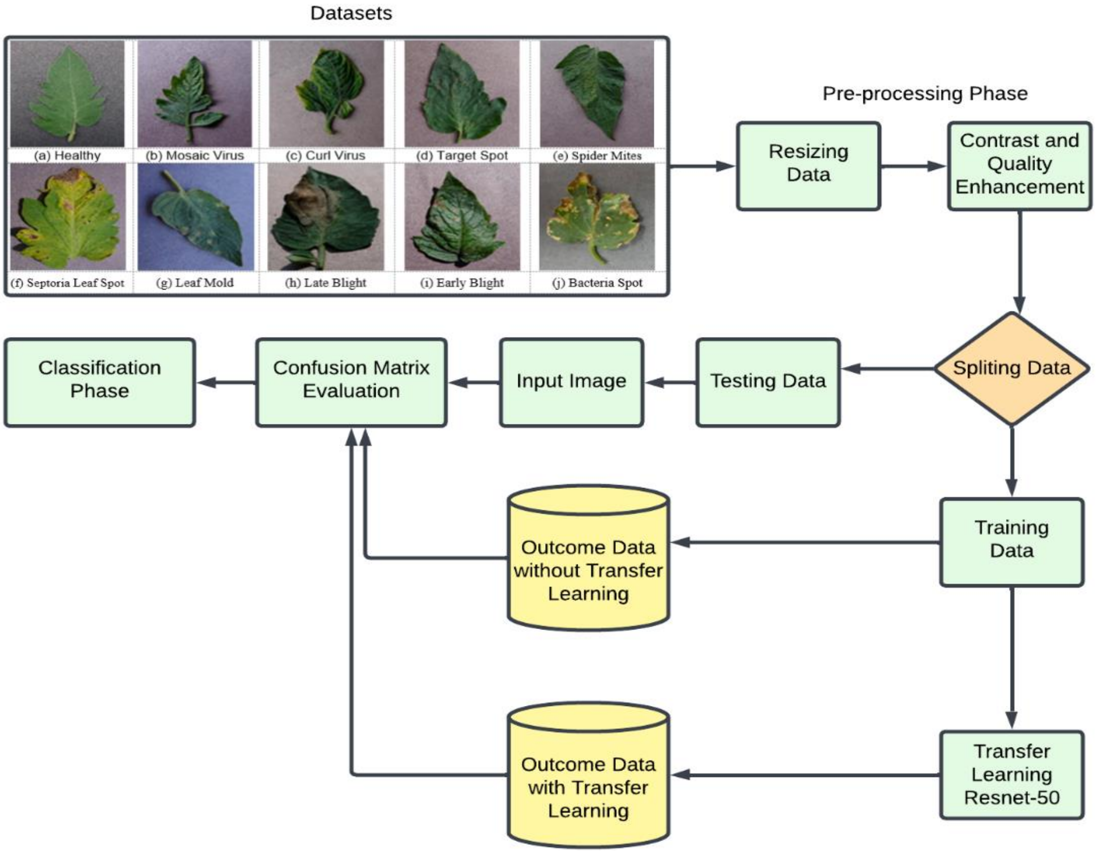


Figure 1. Flow of Proposed Method

2.1 Datasets

The dataset under examination pertains to tomato leaf diseases, encompassing a comprehensive collection of 32,535 meticulously curated images distributed across 10 distinct classes. Prior to analysis, rigorous pre-processing protocols were diligently executed, ensuring the dataset's integrity by eliminating duplicates and standardizing dimensions. Consequently, each image within the dataset exhibits a uniform size of 227 x 227 x 3 pixels. This standardization is paramount, given that Convolutional Neural Network (CNN) architectures necessitate uniformity in input dimensions to facilitate seamless classification processes. By adhering to this standardized size, the research ensures optimal model performance and accuracy, enabling the CNN layers to effectively discern and categorize the intricate visual patterns representative of each tomato leaf disease class. Sample datasets can be seen in Figure 2.

In the preprocessing phase, a rigorous set of methodologies were employed to refine and optimize the dataset for subsequent analyses [4], [18]. Initially, the dataset underwent a pivotal resizing procedure, transitioning images to a standardized dimension to ensure consistency across the board. Following this, contrast and image enhancement techniques were systematically applied to augment the visual clarity and distinguishability of features within each image, thereby enhancing the dataset's overall quality [19]. Moreover, to maintain data integrity and prevent redundancy, a meticulous cleaning process was executed, specifically targeting and eliminating duplicate entries within each class. This strategic approach not only streamlined the dataset but also fortified its reliability, ensuring that subsequent classification tasks would be executed on a refined, high-quality dataset devoid of redundant and extraneous data points.

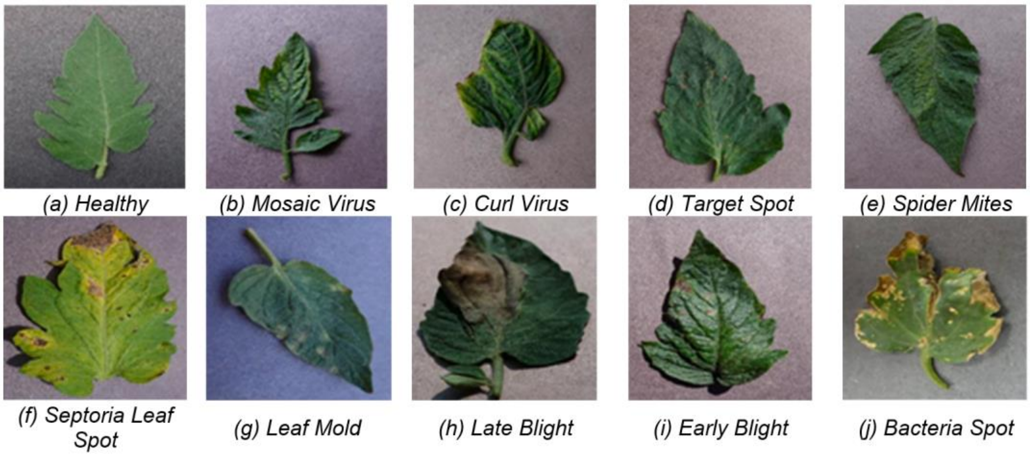


Figure 2. Sample Datasets Per Class

2.2 Convolutional Neural Networks with Resnet-50

Convolutional Neural Networks (CNNs) represent a specialized class of deep learning architectures meticulously designed to excel in tasks related to image recognition and processing [5], [19]. Distinctively structured with convolutional layers that leverage localized spatial hierarchies present in images, CNNs can automatically and adaptively learn spatial hierarchies of features from the raw pixel data. This hierarchical learning process enables the network to identify intricate patterns, textures, and features at varying levels of abstraction, from simple edges and corners to more complex structures and objects. Additionally, CNNs are fortified with pooling layers that reduce spatial dimensions, thereby enhancing computational efficiency and extracting salient features. Furthermore, the incorporation of fully connected layers facilitates the final classification or regression tasks based on the extracted features. Furthermore, the combination of CNNs and transfer learning facilitates the extraction of hierarchical features, enabling the model to achieve superior classification outcomes while optimizing computational resources and training time [22], [23]. CNN layers based on Transfer Learning Resnet-50 can be seen in Figure 3.

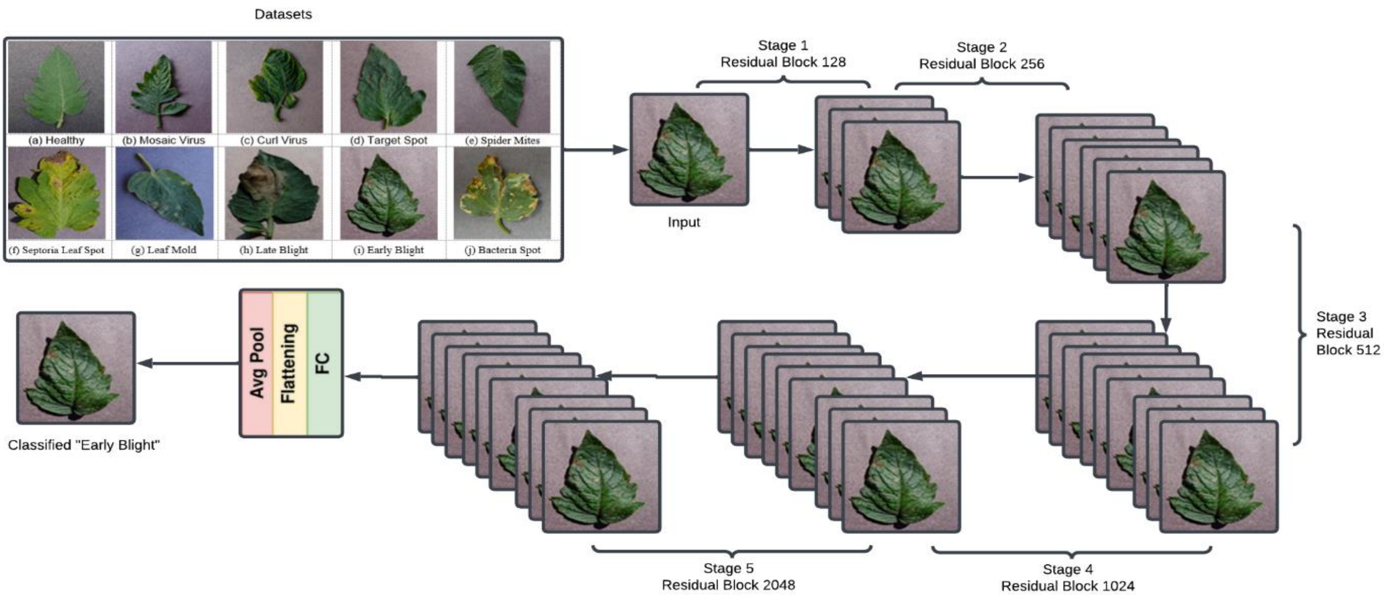


Figure 3. Resnet-50 Layers Per Stage

The utilization of Convolutional Neural Networks (CNNs) coupled with transfer learning, specifically leveraging the ResNet-50 architecture, represents a sophisticated approach in the realm of deep learning-based image classification [19]–[21]. The ResNet-50, a pre-trained model, brings forth a wealth of learned features from extensive datasets, thereby expediting the training process and enhancing model performance. By employing transfer learning, the foundational knowledge embedded within ResNet-50 is harnessed and fine-tuned to cater to the nuances of the specific classification task at hand. This synergistic integration not only accelerates convergence during the training phase but also ensures robustness and accuracy, allowing the model to adeptly discern intricate patterns within the dataset.

2.3 Confusion Matrix Evaluation

Confusion matrix evaluation serves as a pivotal metric in gauging the efficacy and performance of classification models, particularly when discerning intricate patterns associated with tomato leaf diseases. This matrix provides a comprehensive breakdown of true positive, true negative, false positive, and false negative predictions, enabling researchers to quantify the model's accuracy, precision, recall, and F1-score across various disease categories [24], [25]. By meticulously analyzing the confusion matrix, one can identify potential misclassifications or areas of improvement within the model's classification framework. Specifically, for tomato leaf disease classification, the matrix elucidates the model's proficiency in distinguishing between different disease classes, thereby facilitating informed decisions regarding disease management strategies and ensuring optimal crop health. Through this evaluative lens, the confusion matrix not only validates the model's robustness but also underscores its practical applicability in real-world agricultural contexts. Based on confusion matrix evaluation, equation can be seen in Equation 1 to Equation 4.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision \times Recall} \tag{4}$$

Firstly, the accuracy metric (Equation 1) quantifies the model's overall correctness by gauging the ratio of correctly predicted observations (both true positives, TP, and true negatives, TN) to the total number of predictions. Secondly, precision (Equation 2) offers insights into the model's exactness, focusing specifically on the proportion of true positive predictions relative to the combined true positives and false positives (FP). Concurrently, recall (Equation 3) emphasizes the model's completeness, capturing the ratio of true positive predictions to the aggregate of true positives and false negatives (FN). Lastly, the F1-Score (Equation 4) harmoniously amalgamates precision and recall into a singular metric, offering a balanced assessment by taking their harmonic mean, ensuring that both false positives and false negatives are equally weighted.

3. Results and Discussion

During the testing phase, the evaluation was meticulously conducted utilizing MATLAB 2020b, leveraging its comprehensive suite of analytical tools and functionalities tailored for deep learning applications. The computational infrastructure supporting this endeavor was anchored by a robust hardware configuration featuring an Intel Core i3 10th Generation processor, ensuring swift data processing and model inference. Furthermore, the system was bolstered by an NVIDIA MX 330 graphics processing unit (GPU), optimizing parallel computations and accelerating the training and testing workflows. The efficiency of data retrieval and storage was enhanced by a solid-state drive (SSD) with a generous capacity of 256 GB, facilitating rapid data access and seamless model operations. Complementing this hardware ensemble, a substantial 16 GB RAM allocation fortified the system's multitasking capabilities, ensuring uninterrupted performance and expedited analyses throughout the rigorous testing phase.

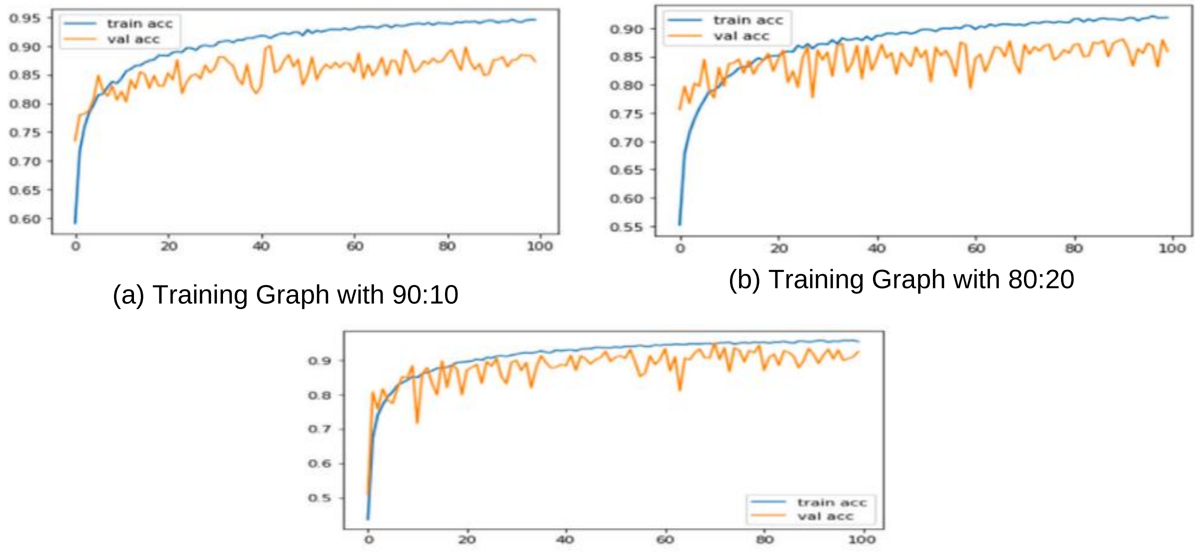
Based on the aforementioned algorithm, the training phase was systematically executed, partitioning the dataset into three distinct testing splits: a 90:10 ratio, an 80:20 ratio, and a 70:30 ratio for training and validation, respectively. This strategic partitioning enabled a comprehensive evaluation of the model's performance across varying data distributions, ensuring robustness and generalizability. Subsequent to training, a graphical representation, as depicted in Figure 4, was generated to visualize the model's training dynamics, elucidating key metrics such as loss and accuracy across epochs. In Figure 4, the depicted graphical representation captures the training dynamics of the model, specifically employing the ResNet-50 architecture.

Table 1. Algorithm based on CNN with Resnet-50 and Hiperparameter

Algorithm: CNN with Resnet-50 Layers and Hiperparameter
Input: Image of size $227x227x3$ **Initialize CNN layers:**

Convolutional Layer: $64\ filters, kernel\ size\ 7x7, stride\ 2, padding\ 'same'$
MaxPooling Layer: $Pool\ size\ 3x3, stride\ 2$
Stage 1 (Residual Block 128):
Convolutional Layer: $128\ filters, kernel\ size\ 3x3, padding\ 'same'$
MaxPooling Layer: $Pool\ size\ 3x3, stride\ 2$
Stage 2 (Residual Block 256):
Convolutional Layer: $256\ filters, kernel\ size\ 3x3, padding\ 'same'$
MaxPooling Layer: $Pool\ size\ 3x3, stride\ 2$
Stage 3 (Residual Block 512):
Convolutional Layer: $512\ filters, kernel\ size\ 3x3, padding\ 'same'$
MaxPooling Layer: $Pool\ size\ 3x3, stride\ 2$
Stage 4 (Residual Block 1024):
Convolutional Layer: $1024\ filters, kernel\ size\ 3x3, padding\ 'same'$
MaxPooling Layer: $Pool\ size\ 3x3, stride\ 2$
Stage 5 (Residual Block 2048):
Convolutional Layer: $2048\ filters, kernel\ size\ 3x3, padding\ 'same'$
MaxPooling Layer: $Pool\ size\ 3x3, stride\ 2$
Activation Function: $ReLU$
Dropout: $20\% \leftarrow 0.2$
Global Average Pooling Layer
Fully Connected Layer: Neurons equal to the number of classes $\leftarrow 10\ Class$
Activation Function: $Softmax$
Compile the Model:
Optimizer: $Adam$
Learning rate(s): 0.0001
Loss Function: Categorical Crossentropy
Set Batch Size: 32
Train the Model using the specified hyperparameters.

Upon obtaining the training graph, as illustrated in Figure 4, a subsequent phase of evaluation was conducted to rigorously assess the model's classification prowess. This evaluation was intricately captured and represented through a confusion matrix, delineating the model's predictions against actual classifications for each disease category. Table 2 encapsulates this comprehensive evaluation, providing a granular breakdown of true positives, true negatives, false positives, and false negatives across the distinct disease classes.



(a) Training Graph with 90:10
(b) Training Graph with 80:20
(c) Training Graph with 70:30
Figure 4. Training Graph Based on Resnet-50

Table 2. Evalution Results Based on Confusion Matrix

Evaluation Phase	Split Data	Accuracy	Recall	Precision	F1-Score
Base CNN (Without Resnet-50)	90:10	95.19%	98%	99%	98.50%
	80:20	95.88%	98%	99%	98.50%
	70:30	94.94%	98%	99%	98.50%
Proposed Method (With Resnet-50)	90:10	99.96%	99.80%	99.80%	99.81%
	80:20	99.98%	99.98%	99.92%	99.96%
	70:30	99.96%	99.82%	99.78%	99.81%

The tabulated data provides a comparative analysis between two distinct methodologies for tomato leaf disease classification: the Base CNN without ResNet-50 and the Proposed Method incorporating ResNet-50. When examining the Base CNN model across different data splits (90:10, 80:20, and 70:30), the accuracy remains commendably high, hovering around the mid to high 90% range. Notably, across all splits, the recall, precision, and F1-score metrics consistently maintain optimal values, showcasing the model's proficiency in both sensitivity and positive predictive value.

Conversely, the introduction of ResNet-50 in the Proposed Method elevates the classification performance to unparalleled levels. Across all data splits, the Proposed Method achieves near-perfect accuracy metrics, surpassing 99%. Moreover, the recall, precision, and F1-score metrics within this methodology approach or achieve perfect scores, underscoring the ResNet-50's efficacy in enhancing the model's ability to correctly identify and classify tomato leaf diseases. In essence, the data vividly underscores the transformative impact of integrating ResNet-50, as it not only augments accuracy but also refines the model's precision and recall, culminating in a more robust and reliable classification framework compared to the Base CNN model.

Table 3. Comparison with Other Researches

Research	Novelty	Accuracy	Recall	Precision	F1-Score
Maeda et al. [14]	CNN with GoogLeNet	99.72%	99.12%	99.29%	99.20%
Paul et al. [15]	CNN with VGGNet	95% (Best Model)	95%	95%	95%
Chen et al. [16]	CNN with AlexNet	96%	95%	98%	97%
Sembiring et al. [17]	CNN with VGGNet	98.28%	-	-	-
Proposed Method	**CNN with Resnet-50**	**99.97% (Average)**	**99.87%**	**99.86%**	**99.88%**

Table 3 presents a comprehensive comparison between the proposed method utilizing CNN with ResNet-50 and other seminal researches endeavors that employed various convolutional neural network architectures for tomato leaf disease classification. Maeda et al. [1] utilized CNN with GoogLeNet, achieving commendable metrics with an accuracy of 99.72%, recall of 99.12%, precision of 99.29%, and an F1-Score of 99.20%. Paul et al. [2] leveraged CNN with VGGNet, marking their best model with an accuracy of 95%, which aligns with their metrics across recall, precision, and F1-Score. Chen et al. [3] employed CNN with AlexNet, securing a 96% accuracy, 95% recall, 98% precision, and a notable 97% F1-Score. Sembiring et al. [4] also utilized VGGNet, achieving an accuracy of 98.28%; however, specific recall and precision metrics were not provided. In comparison, the proposed method in this study, implementing CNN with ResNet-50, demonstrates superior performance metrics with an average accuracy of 99.97%, recall of 99.87%, precision of 99.86%, and an F1-Score of 99.88%. This comprehensive evaluation underscores the efficacy and advancements introduced by the ResNet-50 architecture in enhancing the classification accuracy and reliability for tomato leaf disease detection.

4. Conclusion

In the comparative evaluation between the Base CNN model without ResNet-50 and the Proposed Method leveraging ResNet-50 for tomato leaf disease classification, the results manifest a substantial enhancement in performance metrics with the integration of ResNet-50. Across varying data splits of 90:10, 80:20, and 70:30, the Proposed Method consistently outperformed the Base CNN model, achieving remarkable accuracy metrics of 99.96%, 99.98%, and 99.96%, respectively. Furthermore, the incorporation of ResNet-50 markedly improved recall, precision, and F1-Score, underscoring its pivotal role in refining the model's sensitivity and positive predictive value. Consequently, these findings corroborate the unparalleled efficacy of ResNet-50 in augmenting the accuracy and reliability of tomato leaf disease classification, reaffirming its significance in advancing agricultural diagnostics and facilitating informed decision-making processes for farmers and stakeholders.

Although the integration of ResNet-50 has demonstrated remarkable advancements in tomato leaf disease classification, future research endeavors could delve deeper into several avenues to further refine and optimize the model's performance. Firstly, exploring ensemble techniques by combining multiple state-of-the-art architectures might yield synergistic benefits, potentially enhancing both accuracy and computational efficiency. Additionally, the incorporation of advanced data augmentation strategies and techniques to address potential overfitting can further bolster the model's robustness across diverse environmental and lighting conditions. Moreover, extending the research scope to encompass a broader range of plant diseases or integrating real-time monitoring capabilities for field applications could expand the model's applicability and utility in agricultural settings. Furthermore, collaborative interdisciplinary efforts involving agronomists, biologists, and machine learning experts could facilitate the development of comprehensive diagnostic tools tailored to address the evolving challenges in crop disease management, thereby fostering sustainable agricultural practices and ensuring global food security.

Acknowledgement

Special thanks to University of Dian Nuswantoro who has helped and supporting this experiment. Hopefully this research can be useful for further research.

References

[1] S. V. Mahadevkar *et al.*, “A Review on Machine Learning Styles in Computer Vision - Techniques and Future Directions,” *IEEE Access*, vol. 10. Institute of Electrical and Electronics Engineers Inc., pp. 107293–107329, 2022. https://doi.org/10.1109/ACCESS.2022.3209825
[2] A. A. Khan, A. A. Laghari, and S. A. Awan, “Machine Learning in Computer Vision: A Review,” *EAI Endorsed Transactions on Scalable Information Systems*, vol. 8, no. 32, pp. 1–11, 2021. https://doi.org/10.4108/eai.21-4-2021.169418
[3] D. Bhatt *et al.*, “Cnn variants for computer vision: History, architecture, application, challenges and future scope,” *Electronics (Switzerland)*, vol. 10, no. 20. MDPI, Oct. 01, 2021. https://doi.org/10.3390/electronics10202470
[4] D. Fajri Riesaputri, C. Atika Sari, D. R. Ignatius Moses Setiadi, and E. Hari Rachmawanto, “Classification of Breast Cancer using PNN Classifier based on GLCM Feature Extraction and GMM Segmentation,” in *Proceedings - 2020 International Seminar on Application for Technology of Information and Communication: IT Challenges for Sustainability, Scalability, and Security in the Age of Digital Disruption, iSemantic 2020*, Institute of Electrical and Electronics Engineers Inc., Sep. 2020, pp. 83–87. https://doi.org/10.1109/iSemantic50169.2020.9234207
[5] N. R. D. Cahyo, C. A. Sari, E. H. Rachmawanto, C. Jatmoko, R. R. A. Al-Jawry, and M. A. Alkhafaji, “A Comparison of Multi Class Support Vector Machine vs Deep Convolutional Neural Network for Brain Tumor Classification,” in *2023 International Seminar on Application for Technology of Information and Communication (iSemantic)*, IEEE, Sep. 2023, pp. 358–363. https://doi.org/10.1109/iSemantic59612.2023.10295336
[6] T. Fahey *et al.*, “Active and passive electro-optical sensors for health assessment in food crops,” *Sensors (Switzerland)*, vol. 21, no. 1. MDPI AG, pp. 1–40, Jan. 01, 2021. https://doi.org/10.3390/s21010171
[7] D. P. Roberts, N. M. Short, J. Sill, D. K. Lakshman, X. Hu, and M. Buser, “Precision agriculture and geospatial techniques for sustainable disease control,” *Indian Phytopathology*, vol. 74, no. 2. Springer, pp. 287–305, Jun. 01, 2021. https://doi.org/10.1007/s42360-021-00334-2
[8] A. S. Paymode and V. B. Malode, “Transfer Learning for Multi-Crop Leaf Disease Image Classification using Convolutional Neural Network VGG,” *Artificial Intelligence in Agriculture*, vol. 6, pp. 23–33, Jan. 2022. https://doi.org/10.1016/j.aiia.2021.12.002
[9] C. Umam, D. Andi Krismawan, and R. Raad Ali, “CNN for Image Identification of Hiragana Based on Pattern Recognition,” 2021.
[10] A. S. B. Reddy and D. S. Juliet, “Transfer Learning with ResNet-50 for Malaria Cell-Image Classification,” in *2019 International Conference on Communication and Signal Processing (ICCSP)*, IEEE, Apr. 2019, pp. 0945–0949. https://doi.org/10.1109/ICCSP.2019.8697909
[11] X. X. Li, D. Li, W. X. Ren, and J. S. Zhang, “Loosening Identification of Multi-Bolt Connections Based on Wavelet Transform and ResNet-50 Convolutional Neural Network,” *Sensors*, vol. 22, no. 18, Sep. 2022. https://doi.org/10.3390/s22186825
[12] G. S. Nugraha, M. I. Darmawan, and R. Dwiyansaputra, “Comparison of CNN’s Architecture GoogleNet, AlexNet, VGG-16, Lenet -5, Resnet-50 in Arabic Handwriting Pattern Recognition,” *Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control*, May 2023. https://doi.org/10.22219/kinetik.v8i2.1667
[13] M. Dhanaraju, P. Chenniappan, K. Ramalingam, S. Pazhanivelan, and R. Kaliaperumal, “Smart Farming: Internet of Things (IoT)-Based Sustainable Agriculture,” *Agriculture (Switzerland)*, vol. 12, no. 10. MDPI, Oct. 01, 2022. https://doi.org/10.3390/agriculture12101745
[14] V. Maeda-Gutiérrez *et al.*, “Comparison of convolutional neural network architectures for classification of tomato plant diseases,” *Applied Sciences (Switzerland)*, vol. 10, no. 4, Feb. 2020. https://doi.org/10.3390/app10041245
[15] S. G. Paul *et al.*, “A real-time application-based convolutional neural network approach for tomato leaf disease classification,” *Array*, vol. 19, Sep. 2023. https://doi.org/10.1016/j.array.2023.100313
[16] H. C. Chen *et al.*, “AlexNet Convolutional Neural Network for Disease Detection and Classification of Tomato Leaf,” *Electronics (Switzerland)*, vol. 11, no. 6, Mar. 2022. https://doi.org/10.3390/electronics11060951
[17] A. Sembiring, Y. Away, F. Arnia, and R. Muharar, “Development of Concise Convolutional Neural Network for Tomato Plant Disease Classification Based on Leaf Images,” in *Journal of Physics: Conference Series*, IOP Publishing Ltd, Mar. 2021. https://doi.org/10.1088/1742-6596/1845/1/012009
[18] Z. Azouz, B. Honarvar Shakibaei Asli, and M. Khan, “Evolution of Crack Analysis in Structures Using Image Processing Technique: A Review,” *Electronics (Basel)*, vol. 12, no. 18, p. 3862, Sep. 2023. https://doi.org/10.3390/electronics12183862
[19] M. M. I. Al-Ghiffary, C. A. Sari, E. H. Rachmawanto, N. M. Yacoob, N. R. D. Cahyo, and R. R. Ali, “Milkfish Freshness Classification Using Convolutional Neural Networks Based on Resnet50 Architecture,” *Advance Sustainable Science Engineering and Technology*, vol. 5, no. 3, p. 0230304, Oct. 2023. https://doi.org/10.26877/asset.v5i3.17017
[20] A. Deshpande, V. V. Estrela, and P. Patavardhan, “The DCT-CNN-ResNet50 architecture to classify brain tumors with super-resolution, convolutional neural network, and the ResNet50,” *Neuroscience Informatics*, vol. 1, no. 4, p. 100013, Dec. 2021. https://doi.org/10.1016/j.neuri.2021.100013
[21] S. Showkat and S. Qureshi, “Efficacy of Transfer Learning-based ResNet models in Chest X-ray image classification for detecting COVID-19 Pneumonia,” *Chemometrics and Intelligent Laboratory Systems*, vol. 224, May 2022. https://doi.org/10.1016/j.chemolab.2022.104534

[22] Y. Zheng *et al.*, "Application of transfer learning and ensemble learning in image-level classification for breast histopathology," *Intelligent Medicine*, vol. 3, no. 2, pp. 115–128, May 2023. https://doi.org/10.1016/j.imed.2022.05.004

[23] D. Agarwal, G. Marques, I. de la Torre-Díez, M. A. Franco Martin, B. García Zapiraín, and F. Martín Rodríguez, "Transfer learning for alzheimer's disease through neuroimaging biomarkers: A systematic review," *Sensors*, vol. 21, no. 21. MDPI, Nov. 01, 2021. https://doi.org/10.3390/s21217259

[24] A. Theissler, M. Thomas, M. Burch, and F. Gerschner, "ConfusionVis: Comparative evaluation and selection of multi-class classifiers based on confusion matrices," *Knowl Based Syst*, vol. 247, Jul. 2022. https://doi.org/10.1016/j.knosys.2022.108651

[25] S. R. Waheed, N. M. Suaib, M. S. Mohd Rahim, M. Mundher Adnan, and A. A. Salim, "Deep Learning Algorithms-based Object Detection and Localization Revisited," in *Journal of Physics: Conference Series*, IOP Publishing Ltd, May 2021. https://doi.org/10.1088/1742-6596/1892/1/012001