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OPTIMIZING MULTI-CHANNEL RESNET50 FOR CITRUS LEAF CLASSIFICATION USING COLOR ENHANCEMENT AND EDGE DETECTION METHOD

Handrie Noprisson[1*]; Mariana Purba[2]; Pungkas Subarkah[3]

Department of Informatics[1]
Universitas Dian Nusantara, Jakarta, Indonesia[1]
https://www.undira.ac.id[1]
handrie.noprisson@dosen.undira.ac.id[*]

Department of Informatics[2]
Universitas Sjakhyakirti, Palembang, Indonesia[2]
https://www.unisti.ac.id[2]
mariana_purba@unisti.ac.id[2]

Department of Informatics[3]
Universitas Amikom Purwokerto, Purwokerto, Indonesia[3]
https://amikompurwokerto.ac.id[3]
subarkah@amikompurwokerto.ac.id[3]

(*) Corresponding Author
(Responsible for the Quality of Paper Content)

Abstract— *Conventional methods face limitations due to the high similarity in color and morphology among citrus leaves classification. To address this challenge, deep learning approaches combined with advanced image preprocessing techniques offer a promising solution. This study employed transfer learning using the ResNet50 architecture integrated with image preprocessing methods including contrast enhancement and edge detection. The experiment was implemented in Python 3.13.2 with TensorFlow on an HP OMEN laptop equipped with Intel® Core™ i7-12700F and NVIDIA® GeForce RTX™ 3060 Ti GPU. A dataset of 250 images across five citrus species was captured using a Samsung M54 camera. To enhance dataset diversity, augmentation techniques such as zoom scaling (80–120%), random rotation (±15° to +30°), and horizontal/vertical translation (10–20%) were applied, expanding the dataset to 2,500 images. Data were divided into training (70%), validation (15%), and testing (15%). Four model scenarios were evaluated: MSR-ResNet50 (RGB), GC-ResNet50 (RGB), LF-ResNet50 (GS), and GC-MSR-LF MC-ResNet50 (RGB+GS). Among the evaluated models, GC-MSR-LF MC-ResNet50 achieved the best performance, recording accuracies of 93.7% for training, 91.0% for validation, and 90.2% for the test set. These results indicate a significant improvement in distinguishing citrus leaves with high morphological similarity. The findings confirm that integrating image preprocessing methods with transfer learning enhances the accuracy of citrus leaf classification. The proposed GC-MSR-LF MC-ResNet50 model demonstrates robust generalization across datasets, highlighting its potential application in precision agriculture for automated species identification and crop monitoring.*

Keywords: *citrus leaf, gamma correction, laplacian, multi-scale retinex, resnet50.*

Intisari—*Metode kecerdasan buatan konvensional memiliki keterbatasan dalam mengatasi kesamaan warna dan morfologi untuk proses klasifikasi daun jeruk. Untuk mengatasi tantangan ini, pendekatan deep learning yang dikombinasikan dengan teknik praproses citra dapat menjadi usulan sebagai solusi permasalahan tersebut. Penelitian ini menggunakan transfer learning dengan arsitektur ResNet50 yang terintegrasi dengan metode praproses citra, termasuk peningkatan kontras dan deteksi tepi. Eksperimen diimplementasikan*

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menggunakan Python 3.13.2 dengan TensorFlow pada laptop HP OMEN yang dilengkapi prosesor Intel® Core™ i7-12700F dan GPU NVIDIA® GeForce RTX™ 3060 Ti. Dataset berjumlah 250 citra dari lima spesies jeruk dikumpulkan menggunakan kamera Samsung M54. Untuk meningkatkan keberagaman dataset, diterapkan teknik augmentasi seperti zoom scaling (80–120%), rotasi acak (±15° hingga +30°), serta translasi horizontal/vertikal (10–20%), sehingga dataset menjadi 2.500 citra. Data kemudian dibagi menjadi pelatihan (70%), validasi (15%), dan pengujian (15%). Empat skenario model dievaluasi: MSR-ResNet50 (RGB), GC-ResNet50 (RGB), LF-ResNet50 (GS), dan GC-MSR-LF MC-ResNet50 (RGB+GS). Di antara model yang diuji, GC-MSR-LF MC-ResNet50 menunjukkan performa terbaik dengan akurasi 93,7% pada pelatihan, 91,0% pada validasi, dan 90,2% pada pengujian. Hasil ini menunjukkan peningkatan signifikan dalam membedakan daun jeruk dengan kemiripan morfologi. Hasil penelitian ini menujukkan bahwa integrasi metode praproses citra dengan transfer learning dapat meningkatkan akurasi klasifikasi daun jeruk. Model GC-MSR-LF MC-ResNet50 yang diusulkan menunjukkan hasil generalisasi yang baik pada berbagai dataset, sehingga dapat diterapkan dalam identifikasi dan pemantauan tanaman daun jeruk secara otomatis.

***Kata Kunci**: daun jeruk, gamma correction, laplacian, multi-scale retinex, resnet50.*

INTRODUCTION

Leaf classification is a crucial area in modern agriculture. The most challenging aspect of classification involved distinguishing leaves from species that are closely related, such as those within the citrus genus [1]–[3]. Citrus plants consist of various species, including Citrus aurantiifolia, Citrus limon, Citrus maxima, Citrus microcarpa, and Citrus sinensis. Utilizing technology for their identification could support optimization efforts and improve the processing industry of harvested products [4]–[6].

Deep learning technology had been widely applied in classifying images of leaves from closely related plant species [7], [8]. A significant challenge in classification arose from the similarity in color and shape among different citrus species, necessitating analysis of leaf color, which reflected the physiological condition of the plant, and leaf edges, which exhibited distinct morphological patterns among species [9]–[11].

Recent studies on citrus leaf image classification employed deep learning and image processing techniques to enhance accuracy in differentiating citrus species. For instance, Senthilkumar et al. (2021) utilized a ResNet50 model combined with gamma correction as a contrast enhancement method to improve leaf image quality, thereby achieving better classification accuracy [12]. The study by Luaibi et al. (2021) applied a ResNet50 with data augmentation techniques. The augmentation methods employed included horizontal reflection and image translation to reduce the risk of overfitting during the classification of citrus leaf images [13].

Zhu et al. (2024) utilized ResNet50 with transfer learning and applied histogram equalization to enhance the contrast and clarity of leaf images. This combination aimed to improve the color features of the leaves, making them more easily identifiable by the model [14]. Chowdhury et al. (2024) developed a ResNet50 model utilizing data augmentation and a data split of 70% for training, 15% for validation, and 15% for testing. The original dataset consisted of 596 images, which increased to 2800 images after augmentation [15]. Goyal and Lakhwani (2025) applied Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance the local contrast of leaf images, clarifying important morphological features without introducing excessive noise. Using ResNet50, they achieved a classification accuracy of 84.58% [16].

Previous studies demonstrated that the use of transfer learning models, contrast enhancement techniques, and edge detection methods can highlight distinct color and morphological patterns among species, particularly for leaf images with similar shapes [17]–[19]. However, only a few studies have investigated the combined use of color feature analysis and edge features for citrus leaf image classification [20], [21]. This study aims to improve the classification performance of ResNet50 by integrating image processing techniques, including Gamma Correction (GC) and Multi-Scale Retinex (MSR) on Red, Green, Blue (RGB) images for contrast enhancement [22]–[24], as well as applying the Laplacian filter on grayscale (GS) images to emphasize leaf edge contours that serve as key morphological features [25]–[27].

The deep learning model used was ResNet50, modified to accept a 4-channel input, referred to as Multi-Channel ResNet50. This input consisted of three channels representing color-processed images (enhanced with GC and MSR) and one channel highlighting leaf edges obtained via the Laplacian filter. This approach aimed to maximize feature extraction from leaf color, which reflected the physiological condition of the plant, and leaf

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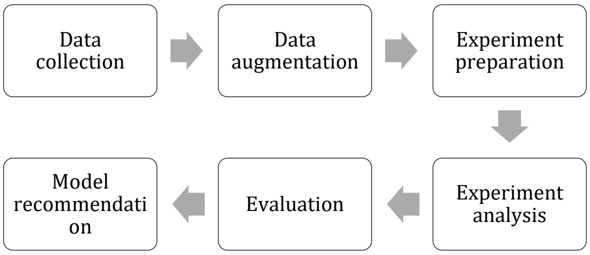
edges, which exhibit distinct morphological patterns among species, thereby enabling accurate classification of citrus leaf types.

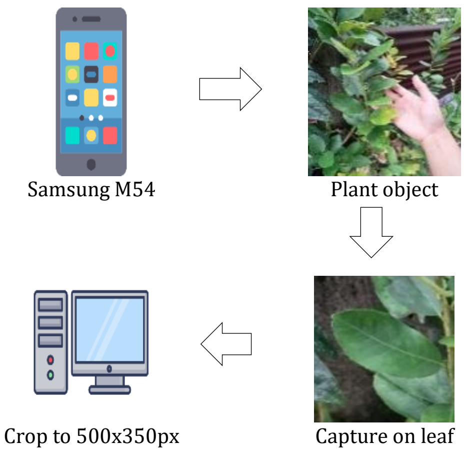
MATERIALS AND METHODS

The study involved experimental scenarios applied to the ResNet50 model, including the use of Multi-Scale Retinex (MSR), Gamma Correction (GC), and Laplacian Filter (LF). Evaluations were conducted based on classification accuracy and confusion matrix for each model. Subsequently, model recommendations were made based on the evaluation results, selecting the base ResNet50 model that achieved the highest accuracy. The overall research stages are illustrated in Fig. 1.



Source : (Research Results, 2025)
Figure 1. Research phase

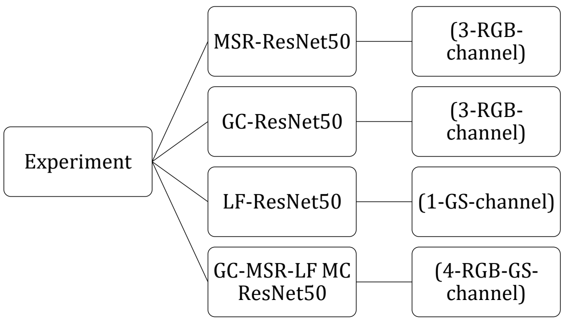
The experiment was prepared and conducted using Python 3.13.2 and TensorFlow with a double-channel ResNet50 model. The experiment was used an HP OMEN laptop with an Intel® Core™ i7-12700F processor and an NVIDIA® GeForce RTX™ 3060 Ti (GDDR6) GPU. Data collection was performed using a Samsung M54 camera, capturing five classes of citrus leaf images, including Citrus aurantiifolia, Citrus limon, Citrus maxima, Citrus microcarpa, and Citrus sinensis as depicted in Fig. 2.



Source : (Research Results, 2025)
Figure 2. Data collection of citrus leaf

Data augmentation was applied to the citrus leaf images by configuring zoom parameters within a range of 0.8 to 1.2, allowing the images to be scaled between 80% and 120% of their original size. Random rotations were performed within an angle range of -15 to +30 degrees to enable the model to recognize images from various orientations. Additionally, image translation was implemented both horizontally and vertically, shifting the images by 10% to 20% of their width and height, respectively, in order to train the model to handle object positioning variability within the images. The dataset consisted of five classes. Each class contained 50 citrus leaf images and after the augmentation process, the number of images per class increased to 500, resulting in a total of 2,500 images in the dataset.

The experiment was conducted using ResNet50 base model with various image processing methods and input channel configurations. The first scenario, MSR-ResNet50, utilized three-channel RGB images enhanced with MSR for contrast improvement. The GC-ResNet50 scenario applied GC to the RGB images to enhance lighting conditions. The LF-ResNet50 scenario used a single grayscale (GS) channel processed with a LF to emphasize object edges. The final scenario, GC-MSR-LF-MCResNet50, combined all four channels, including three RGB channels processed with GC and MSR, along with one GS channel derived from the LF applied to the GC-MSR images. A summary of experiment scenarios is illustrated in Fig. 3.



Source : (Research Results, 2025)
Figure 3. Experiment scenario

The evaluation of the double-channel ResNet50 model was conducted by calculating classification accuracy, loss function, and confusion matrix at each stage of training, validation, and testing. From the total of 2,500 images obtained after augmentation, the dataset was split with proportions of 70% for training, 15% for validation, and 15% for testing, resulting in 1,750 training images, 375 validation images, and 375 testing images.

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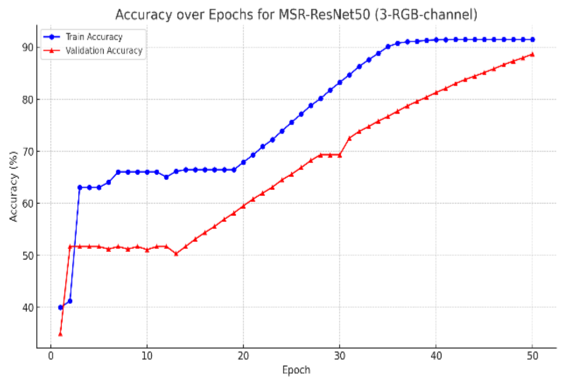
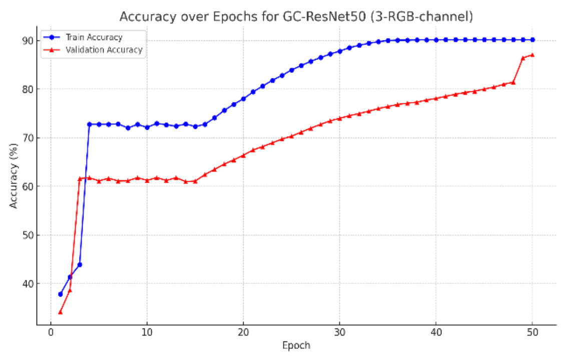
RESULTS AND DISCUSSION

In the study of citrus leaf classification, several model scenarios were evaluated based on different input channel configurations and preprocessing techniques. The MSR-ResNet50 model was implemented using three RGB channels as input, capturing the standard color information of the leaf images. In the citrus leaf classification experiments, the MSR-ResNet50 model, which utilized three RGB channels as input, was trained and validated. During training, the model achieved an accuracy of 91.5%, while on the validation dataset, an accuracy of 88.7% was obtained. The accuracy per epoch in experiment is depicted in Fig. 4.



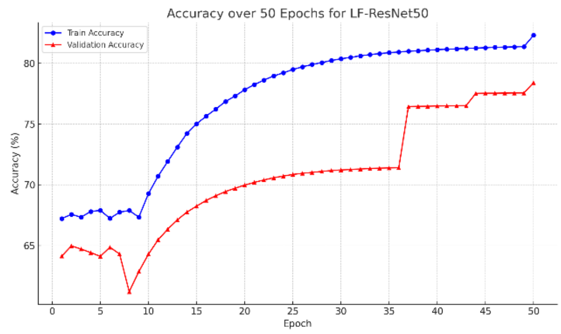
Source : (Research Results, 2025)
Figure 4. Accuracy of MSR-ResNet50

The GC-ResNet50 model also utilized three RGB channels, but incorporated Gamma Correction (GC) preprocessing to enhance image quality prior to classification. The GC-ResNet50 model, which processed three RGB channels with Gamma Correction applied as a preprocessing step, was trained and validated for citrus leaf classification. The model achieved a training accuracy of 90.2% and a validation accuracy of 87.1% as depicted in Fig. 5.



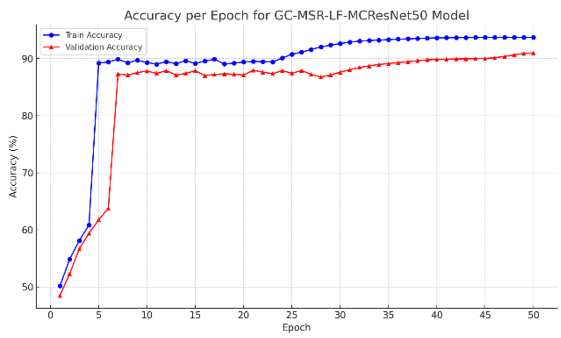
Source : (Research Results, 2025)
Figure 5. Accuracy of GC-ResNet50

For the LF-ResNet50 model, a single grayscale (GS) channel was employed, focusing on texture and intensity features without color information. The LF-ResNet50 model, which utilized a single grayscale (GS) channel as input, was trained and validated for the classification of citrus leaf images. The model achieved a training accuracy of 82.3% and a validation accuracy of 78.4%, as depicted in Fig. 6.



Source : (Research Results, 2025)
Figure 6. Accuracy of LF-ResNet50

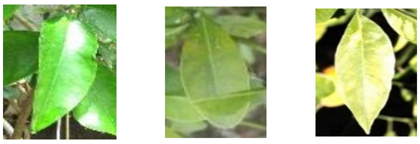
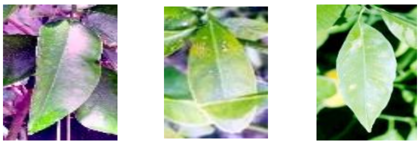
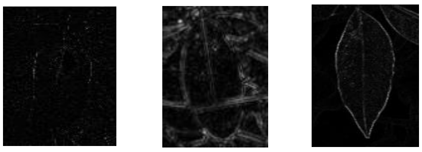
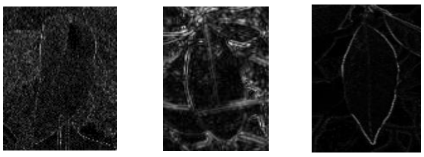
The GC-MSR-LF MC-ResNet50 model, which combined four input channels consisting of three RGB channels and one grayscale (GS) channel integrated with Gamma Correction, Multi-Scale Retinex, and Laplacian Filter (LF) preprocessing techniques, was trained and validated for citrus leaf classification. The model achieved a training accuracy of 93.7% and a validation accuracy of 91.0%, as depicted in Fig. 7.



Source : (Research Results, 2025)
Figure 7. Accuracy of GC-MSR-LF-MCResNet50

The raw image of citrus leaf was obtained without any enhancement process, resulting in uneven illumination and suboptimal contrast. The method of Gamma Correction (GC) was applied to the citrus leaf, for example *Citrus microcarpa* leaf to enhance brightness and contrast by non-linearly adjusting pixel intensity values. The method of Multi-Scale Retinex (MSR) was employed on the citrus leaf image to improve illumination and balance local contrast. Then, the Laplacian filter (LF) was utilized to sharpen edges and emphasize fine detail features by detecting changes in pixel intensity of citrus leaf. The combination of MSR with GC and LF was applied to citrus leaf image, resulting in grayscale (GS) image. The example of image processing result for every method is depicted in Table 1.

Table 1. Example of image processing result

Method	*Citrus aurantiifolia*	*Citrus microcarpa*	*Citrus sinensis*
Raw			
GC			
MSR			
LF			
GC MSR LF			

Source : (Research Results, 2025)

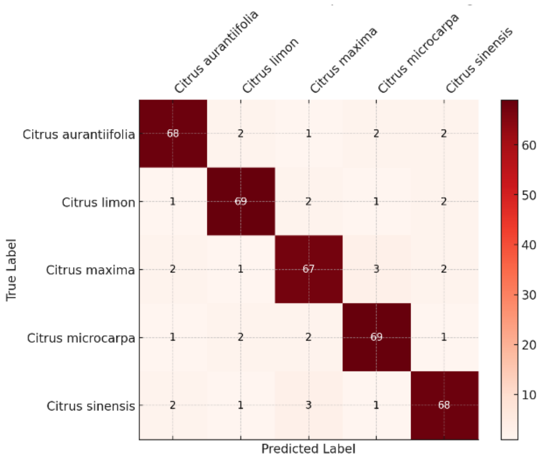
The performance of each model was evaluated on the test dataset for citrus leaf classification. The MSR-ResNet50 model, using three RGB channels, achieved a test accuracy of 87.3%. The GC-ResNet50 model, which incorporated Gamma Correction (GC) on three RGB channels, reached a test accuracy of 85.9%. The LF-ResNet50 model, utilizing a single grayscale channel, obtained a lower test accuracy of 76.8%, reflecting the limited information from intensity-only images. The GC-MSR-LF MC-ResNet50 model, which combined four channels (three RGB and one grayscale) along with multiple preprocessing techniques, demonstrated the highest test accuracy of 90.2%, confirming the advantage of integrating multi-channel inputs and enhancement methods for improved classification performance. The complete result of experiment is presented in Table 2.

Table 2. Experiment result

Scenario	Train	Val	Test
CNN	86.1%	83.1%	82.6%
MSR-CNN (3-RGB-channel)	88.3%	85.5%	84.2%
MSR-ResNet50 (3-RGB-channel)	91.5%	88.7%	87.3%
GC-ResNet50 (3-RGB-channel)	90.2%	87.1%	85.9%
LF-ResNet50 (1-GS-channel)	82.3%	78.4%	76.8%
GC-MSR-LF MC-ResNet50 (4-RGB-GS-channel)	93.7%	91.0%	90.2%

Source : (Research Results, 2025)

In the confusion matrix, the first row corresponding to the *Citrus aurantifolia* class indicated that out of the data truly labeled as *Citrus aurantifolia*, 68 images were correctly classified as Citrus aurantifolia on the main diagonal. Then, 2 images were misclassified as *Citrus limon*, 1 image as *Citrus maxima*, and 2 images as *Citrus sinensis*. The second row, representing the *Citrus limon* class, showed that 69 images were correctly classified as *Citrus limon*. The complete classification can be seen Fig. 8.



Source : (Research Results, 2025)
Figure 8. Confusion matrix of GC-MSR-LF MC-ResNet50

In model of GC-MSR-LF, the kernel size of 3x3 was used for convolution operations, with border handling performed using the default method specified by cv2.BORDER_DEFAULT. Input images for citrus leaf classification were provided either in grayscale or after undergoing preprocessing steps. The image depth was set to cv2.CV_64F to preserve fine detail throughout processing. Postprocessing involved computing the absolute values followed by normalization to standardize the output. The classification model employed was a pretrained ResNet50, which was modified to accept inputs with the shape (B, 4, 224, 224), accommodating four

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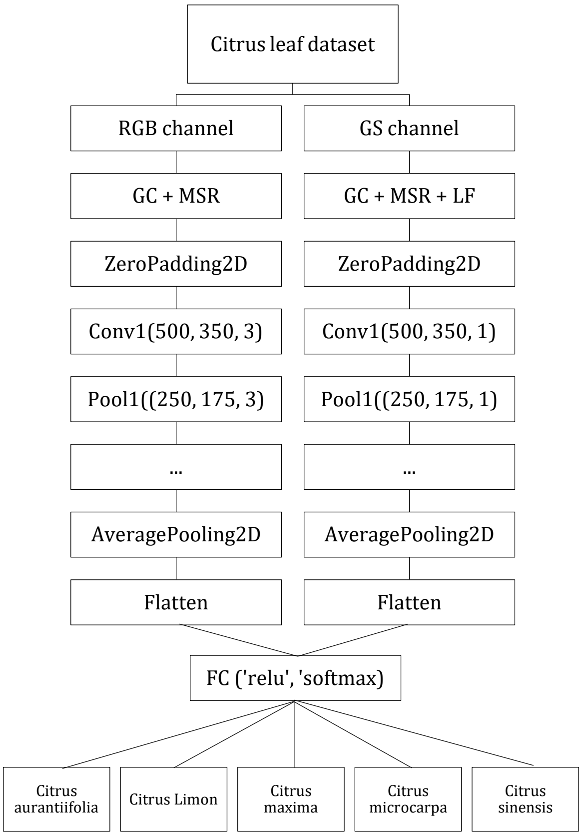
channels corresponding to MSR and Laplacian-filtered images, specifically to improve the classification accuracy of citrus leaf diseases. The proposed architecture of GC-MSR-LF MC-ResNet50 is presented in Fig. 9.



Source : (Research Results, 2025)
Figure 9. Multi-Channel ResNet50

CONCLUSION

The aim of this research was to improve the accuracy of citrus leaf classification by evaluating the effectiveness of various deep learning models combined with advanced image preprocessing techniques. The experiment was conducted using Python 3.13.2 and TensorFlow. A dataset consisting of five class, including *Citrus aurantiifolia*, *Citrus limon*, *Citrus maxima*, *Citrus microcarpa*, and *Citrus sinensis* that was collected via a Samsung M54 camera. Data augmentation techniques such as zoom scaling (80%-120%), random rotations (±15 to +30 degrees), and horizontal and vertical translations (10%-20%) were applied, expanding the original 250-image dataset to 2,500 images. The dataset was split into training (70%), validation (15%), and testing (15%) subsets. A pretrained ResNet50 model was modified to accept inputs shaped (B, 4, 224, 224), accommodating four channels including GC, MSR and LF images to enhance classification accuracy. Four scenarios were evaluated, including MSR-ResNet50 (RGB channels), GC-ResNet50 (RGB channel), LF-ResNet50 (Grayscale channel), and GC-MSR-LF MC-ResNet50 (4 channels, RGB channel and Grayscale channel). The GC-MSR-LF MC-ResNet50 model achieved the highest accuracies of 93.7%, 91.0%, and 90.2% on training, validation, and test sets, respectively, demonstrating the effectiveness of multi-channel inputs and advanced preprocessing for citrus leaf classification. Future research can explore larger and more diverse citrus leaf datasets collected under varying environmental conditions to improve model generalizability. Integration of other deep learning architectures such as EfficientNet or Vision Transformers may further enhance classification performance.

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Accredited Rank 2 (Sinta 2) based on the Decree of the Dirjen Penguatan RisBang Kemenristekdikti No.225/E/KPT/2022, December 07, 2022. Published by LPPM Universitas Nusa Mandiri