
Implementation of ResNet50 Based on Transfer Learning for Sugarcane Leaf Disease Detection

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Abstract

Sugarcane (*Saccharum officinarum*) is a vital commodity in Indonesia's sugar industry and is highly susceptible to leaf diseases such as Mosaic, RedRot, Rust, and Yellow, which significantly reduce yield quality and quantity. This study proposes an automatic disease classification system using the ResNet50 architecture with a transfer learning approach, offering a more systematic evaluation compared to previous studies that typically tested only a single configuration or focused on other crops. The dataset consists of 3,250 RGB images across five classes after preprocessing and augmentation to address class imbalance. Eight model configurations were evaluated by combining epoch values (20, 40) and learning rates (0.0001, 0.001, 0.01, 0.1). The best performance was achieved by the configuration with 20 epochs and a learning rate of 0.0001, producing an accuracy and F1-score of 97%. The model was further deployed into a Flask-based web application to demonstrate practical usability. However, this study is limited by the use of a single controlled dataset, so model performance may vary under real-field conditions such as different lighting, camera angles, and leaf damage severity. Future research should include field data evaluation to strengthen model generalization.

Keywords: *convolutional neural network, resnet50, sugarcane leaf, image classification, disease detection*

INTRODUCTION

Sugarcane (*Saccharum officinarum*) is a strategic commodity in Indonesia's sugar industry. However, productivity often declines due to leaf diseases such as Mosaic, RedRot, Rust, and Yellow, which reduce crop quality and yield (Muliasari & Trilaksono, 2021). Manual inspection conducted by farmers is time-consuming, subjective, and difficult to apply consistently on a large scale, thus requiring automated detection systems that are fast and reliable (Hassan & Maji, 2022). This condition underscores the importance of developing accurate and practical technological solutions to support early disease detection in sugarcane plantations.

Previous research has utilized several machine learning techniques such as Support Vector Machine (SVM) (Manavalan, 2021) and K-Nearest Neighbors (KNN) (Kavitha & Krishna Prasad, 2024). Although these methods provided satisfactory results, their heavy reliance on handcrafted features limits their robustness in handling complex leaf textures and subtle disease symptoms. The emergence of Convolutional Neural Networks (CNNs) offers a more reliable approach through automatic hierarchical feature extraction, leading to superior classification accuracy in various plant disease studies (Sholihin et al., 2023). However, existing CNN-based studies often focus on other crops or experiment with only a single architecture, leaving limited insight into how different configurations affect performance specifically on sugarcane leaves.

Transfer learning has become an effective strategy for addressing dataset limitations by utilizing pre-trained CNN models such as VGG16, VGG19, Inception, or EfficientNet. (Pratitis et al., 2023) achieved high accuracy using VGG16, while (Daphal & Koli, 2024) integrated deep learning models into mobile applications for sugarcane classification. Despite these advances, deeper architectures like VGG tend to have large parameter sizes and high computational costs, which may not be ideal for practical deployment. Furthermore, previous studies rarely investigate multiple hyperparameter variations, resulting in limited understanding of model stability, overfitting behavior, and generalization capability.

ResNet50, with its residual learning mechanism, has proven effective for deep image classification tasks because it reduces vanishing gradient issues while maintaining computational efficiency. Although several agricultural studies have adopted transfer learning using ResNet-based models, systematic evaluation of ResNet50 for sugarcane disease detection across different hyperparameter settings remains scarce. Additionally, few studies extend their work beyond accuracy reporting toward real-world implementation.

To address these gaps, this research systematically evaluates the performance of the ResNet50 architecture using eight combinations of epochs and learning rates to determine the optimal configuration for sugarcane leaf disease classification. Beyond theoretical analysis, the best-performing model is deployed into a Flask-based web application to support real-time diagnosis, providing a practical contribution for precision agriculture and facilitating early detection for farmers. This integrated approach not only strengthens model evaluation but also enhances its applicability in actual agricultural environments.

METHOD

This study uses a quantitative experimental design with a deep learning approach based on a Convolutional Neural Network (CNN). The implemented architecture is ResNet50 with a transfer learning method, where the pre-trained weights from ImageNet are adjusted to the number of target classes of the study. The research stages include: (1) dataset collection, (2) data preprocessing and augmentation, (3) modeling using ResNet50, (4) model testing based on evaluation metrics, and (5) implementation of the best model on a Flask-based web application. The general research flow is shown in Figure 1.

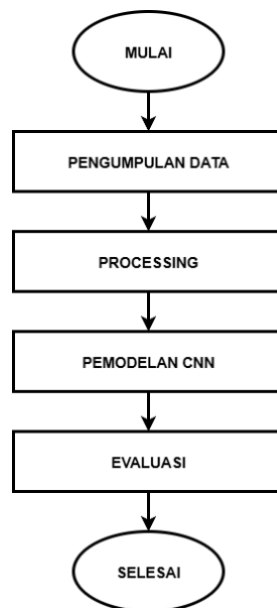


Fig 1. Research Workflow of Sugarcane Leaf Disease Detection

2.1 Data Collection

The research dataset is sourced from the Kaggle platform, namely the Sugarcane Leaf Disease Dataset (<https://www.kaggle.com/datasets/nirmalsankalana/sugarcane-leaf-disease-dataset>), which was previously used by (Daphal & Koli, 2024). The dataset consists of 2,521 RGB images of sugarcane leaves categorized into five classes: Healthy, Mosaic, RedRot, Rust, and Yellow. The initial data distribution is unbalanced, and the raw images exhibit variations in lighting, background, leaf angle, and disease severity, which may influence model generalization. To address this, augmentation and normalization were applied in later stages. Example images are presented in Figure 2.

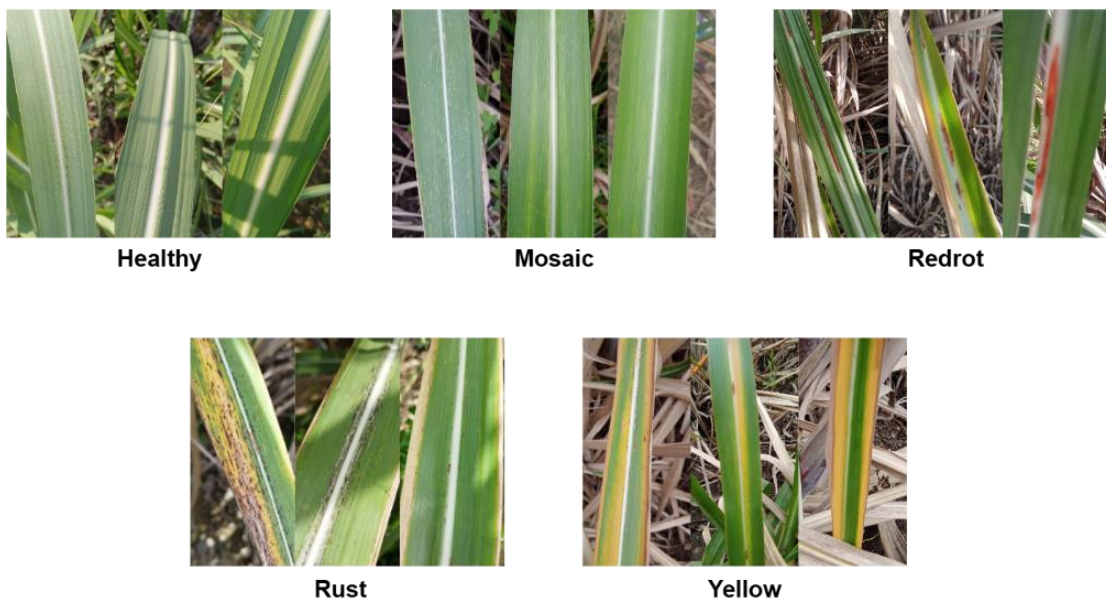


Fig 2. Example images of sugarcane leaves in each class (Healthy, Mosaic, RedRot, Rust, and Yellow)

2.2 Preprocessing

The preprocessing stage was carried out to standardize and improve data quality. These steps included resizing the images to 224×224 pixels, normalizing pixel values to the range $[0,1]$, and data augmentation to balance the class distribution while increasing image variation. The augmentation techniques used included rotation, flipping (horizontal and vertical), and cropping. After augmentation, the number of images in each class was equalized to 650, resulting in a total dataset of 3,250 images. The dataset was then divided into three parts: training data, validation data, and test data, with the distribution shown in Table 1.

Table 1. Distribution Dataset

Kelas	Distribution Dataset			
	Train	Val	Test	Total
Healthy	450	60	140	650
Mosaic	450	60	140	650
RedRot	450	60	140	650
Rust	450	60	140	650
Yellow	450	60	140	650
Total	2.250	300	700	3.250

A fixed data split (train–val–test) was chosen instead of cross-validation because the augmented dataset already met minimum sample requirements per class, while cross-validation would significantly increase computational cost without substantial gain for this dataset size.

2.3 Pre-Trained Model Resnet50

The ResNet50 architecture was employed in this study using a transfer learning approach, where the original fully connected layer was replaced to match the five target classes in the dataset. Several additional layers were incorporated into the model, including a Global Average Pooling layer to reduce the spatial dimensions of the feature maps, a dropout layer with a rate of 0.5 to minimize overfitting, and a Softmax activation function in the output layer to perform multi-class classification.

To examine how optimization choices affect model behavior, eight training configurations were tested by combining two epoch values (20 and 40) with four learning rates (0.0001, 0.001, 0.01, and 0.1). These combinations were designed to analyze the sensitivity of the model to different learning rate scales, observe differences in convergence between shorter and longer training durations, and evaluate the balance between training stability and generalization performance.

The training and experimentation processes in this study were carried out using a local computing device. Providing detailed hardware specifications is important to ensure reproducibility and to allow future researchers to compare computational efficiency under similar conditions. The model training environment used in this research is described as follows:

- Device: VivoBook ASUS X415DAP_M415DA
- Processor: AMD Ryzen 3 3250U with Radeon Graphics (2.60 GHz, 2 cores, 4 logical processors)
- GPU: AMD Radeon Vega 3
- RAM: 16 GB DDR4
- Operating System: Windows 11 Home
- Frameworks: TensorFlow and Keras

This hardware configuration represents a mid-range computing environment, demonstrating that the proposed model can be trained and executed without requiring high-end or server-grade hardware.

The complete workflow of the modified ResNet50 architecture used in this study is illustrated in Figure 3.

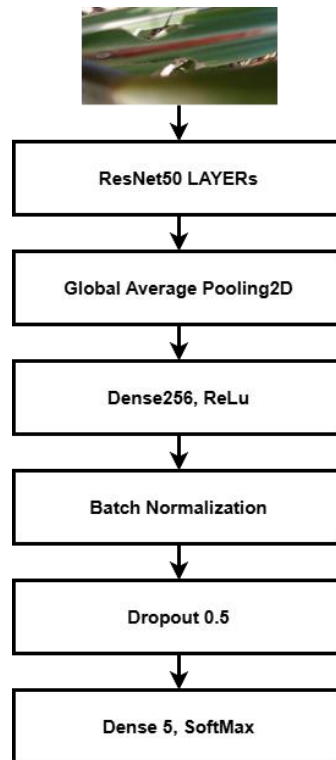


Fig 3. Modified ResNet50 CNN Architecture

2.4 Evaluation Performance

Model performance was evaluated using accuracy, precision, recall, f1-score, and confusion matrix metrics. The calculation equations are shown in (1)–(4) (Sholihin et al., 2025).

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

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

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

$$F1 - Score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (4)$$

RESULTS AND DISCUSSION

3.1 Results

Experiments were conducted on eight ResNet50 model configurations, varying the number of epochs (20 and 40) and learning rate (0.0001, 0.001, 0.01, and 0.1). Performance was evaluated using precision, recall, F1-score, and accuracy. The complete experimental results are shown in Table 2.

Table 2. Performance of the ResNet50 CNN model on eight configurations

Model	Epoch	LR	Evaluation Matrix			
			Precision	Recall	F1-Score	Accuracy
Model 1	20	0.0001	0.97	0.97	0.97	0.97
Model 2	40	0.0001	0.96	0.96	0.96	0.96
Model 3	20	0.001	0.93	0.93	0.93	0.93
Model 4	40	0.001	0.95	0.94	0.94	0.94
Model 5	20	0.01	0.95	0.95	0.95	0.95
Model 6	40	0.01	0.98	0.96	0.96	0.96
Model 7	20	0.1	0.94	0.94	0.94	0.94
Model 8	40	0.1	0.95	0.95	0.95	0.95

From Figure 4 Model 1 (20 epochs, LR = 0.0001) was selected as the best-performing configuration with an accuracy and F1-score of 0.97. This result indicates that a lower learning rate combined with moderate training duration provides better convergence stability and generalization compared to higher learning rates, which tend to produce inconsistent gradients and reduced accuracy.

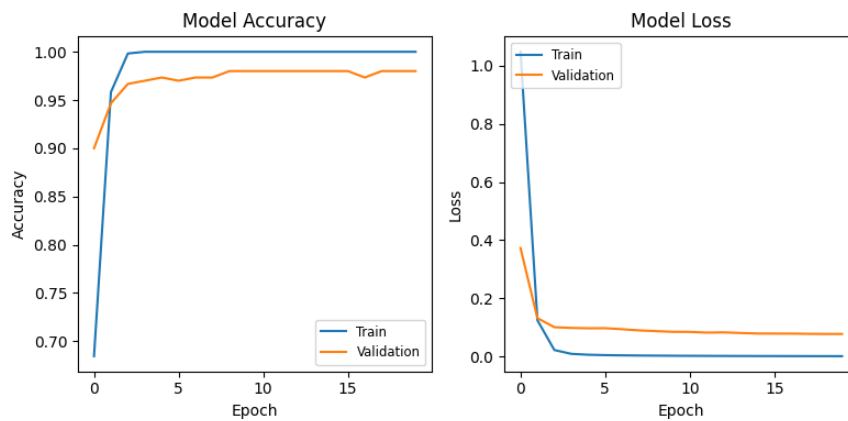


Fig 4. Accuracy and Loss Graph

The accuracy and loss curves for the best-performing model are shown in Figure 5. Training accuracy increased rapidly during early epochs and approached nearly 100%, while validation accuracy stabilized around 97%. This pattern indicates that the model is able to generalize well without significant overfitting. Training loss decreased sharply to near zero, whereas validation loss converged around 0.1, reflecting stable optimization and effective convergence.

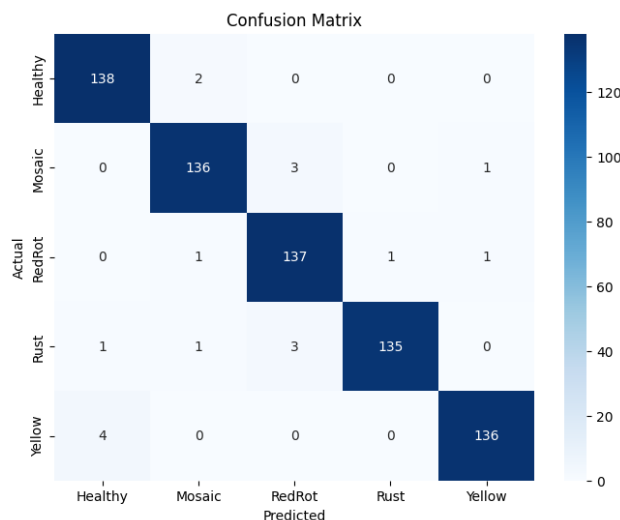


Fig 5. Model 1 Evaluation Metrics

Further evaluation of the test data using a confusion matrix is shown in Figure 5. Per-class metrics are obtained from this matrix, as presented in Table 3.

Table 3. Evaluation per class based on the confusion matrix

Kelas	Precision	Recall	F1-Score	Accuracy
<i>Healthy</i>	0.97	0.99	0.98	0.99
<i>Mosaic</i>	0.97	0.97	0.97	0.99
<i>RedRot</i>	0.96	0.98	0.97	0.99
<i>Rust</i>	0.99	0.96	0.98	0.99
<i>Yellow</i>	0.99	0.97	0.98	0.99

The confusion matrix achieved an accuracy of 97.43%, consistent with the earlier evaluation. All classes demonstrated balanced performance, with no significant prediction failures or class dominance. This suggests that the model performs consistently across all disease categories.

3.2 Discussion

The experimental findings confirm that the ResNet50-based CNN with transfer learning performs highly effectively in sugarcane leaf disease classification. The best model, trained with 20 epochs and a learning rate of 0.0001, achieved a high accuracy of approximately 97%. This result demonstrates that the architecture can extract hierarchical features efficiently despite visual similarities between disease classes.

Although overall performance was strong, several misclassification instances were observed. For example, some Yellow disease images were classified as Healthy. This may occur due to mild discoloration during early infection stages, suboptimal lighting, or low image contrast, which makes symptoms less distinguishable. Small misclassification patterns are also commonly found in plant disease detection research, especially when symptom variations are visually subtle.

Similarly, confusion between Mosaic and Rust likely resulted from overlapping texture patterns or inconsistent image resolution. These findings highlight the need for additional dataset diversity and possibly improved feature localization techniques such as attention mechanisms or Grad-CAM-based refinement.

The training and validation graphs indicate minimal overfitting, supported by the use of dropout and data augmentation. However, since the dataset originates from a controlled Kaggle source, there is a potential risk of dataset bias. Real-world scenarios may introduce variations such as inconsistent lighting, shadow interference, mixed symptoms, or physical leaf damage, which are not fully represented in the current dataset. Thus, future work should involve validation using field images or datasets captured under varied environmental conditions. Incorporating domain adaptation, contrastive learning, or additional augmentation strategies may further improve robustness.

The consistent performance across classes and high evaluation metrics indicate that ResNet50 is a suitable balance between accuracy and computational efficiency. The model's ability to run on mid-range hardware, combined with its integration into a Flask-based web application, highlights its practicality for real-world implementation particularly for assisting farmers in making early disease diagnoses.

3.3 Comparison With Previous Research

To assess the contribution of this research, the model's performance is compared with several previous studies that implemented CNN-based methods and their derivatives. A summary of the comparison results is shown in Table 4.

Table 4. Comparison of Research Results with Previous Dudies

NO	Comparison of Previous Research		
	Research by	Model	Accuracy
1	(Kavitha & Krishna Prasad, 2024)	Ensemble CNN	0.967
2	(C & Verma, 2024)	CNN	0.64
3	(Manavalan, 2021)	VGG-19	0.9984
4	(Pascal & Kunduracioglu, 2024)	DeiT3-Small	0.9379
5	(Patil, 2023)	CNN	0.95
6	(Militante et al., 2019)	CNN	0.95
7	(Pratits et al., 2023)	VGG-16	0.98
8	(Elnursa et al., 2023)	Exception	0.97
9	Proposed CNN	ResNet50, Batch Size=32, Lr=0.0001, Epoch 20	0.97

Overall, the accuracy of the proposed model (0.97) is within the upper range of CNN model performance for plant disease classification. This value is higher than conventional CNNs (0.64–0.95) and comparable to the CNN ensemble approach (0.967) and Exception (0.97). Although the accuracy of VGG16 (0.98) and VGG19 (0.9984) is superior, the complexity of these models is relatively high, which can impact training time and computational requirements.

Compared to the vision-based transformer architecture (DeiT3-Small, 0.9379), ResNet50 provides higher accuracy with a relatively efficient configuration. Thus, ResNet50 is competitive in terms of accuracy and more practical for implementation in web-based applications aimed at supporting farmers in rapidly diagnosing sugarcane diseases.

3.4 Implementation

The main advantage of this research lies in implementing the model into a web-based application using the Flask framework. This application supports three input modes: image upload, direct camera capture, and live camera mode show in Figure 6. Thus, the system can be used practically in the laboratory and the field. This implementation strengthens the research's contribution, as it goes beyond achieving high accuracy and provides applicable solutions in precision agriculture.

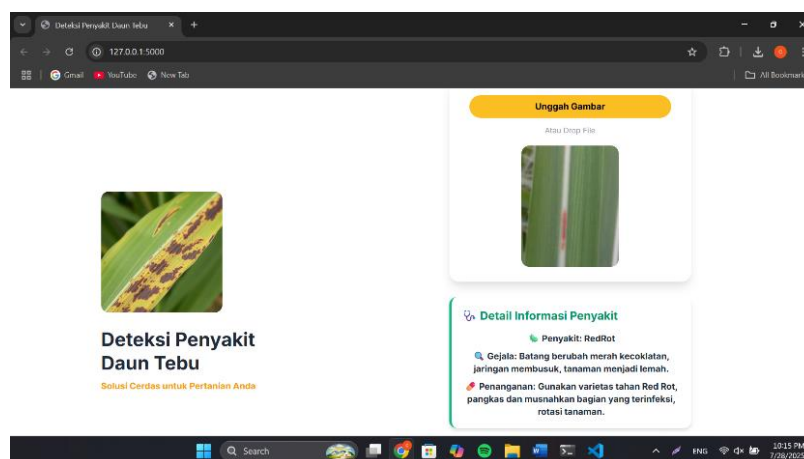


Fig 6. Website Implementation

Although the results demonstrate promising performance, this study still has limitations. Testing was conducted on a dataset under controlled conditions, so the model's performance was not thoroughly tested under real-world conditions with varying light intensity, shooting angles, or partially damaged leaves.

Therefore, further research needs to focus on: testing the system's robustness under real-world conditions, developing a more diverse dataset to strengthen the model's generalizability, and integrating it with Internet of Things (IoT)-based technologies to support the implementation of sustainable smart farming. With these development directions, the ResNet50-based sugarcane leaf disease classification system can potentially become critical in supporting efficient, precise, and sustainable modern agricultural practices

CONCLUSIONS

This study demonstrates that the application of a Convolutional Neural Network (CNN) with the ResNet50 architecture can accurately detect five categories of sugarcane leaf diseases—Healthy, Mosaic, RedRot, Rust, and Yellow—from image data. Among the eight configurations tested, the model trained with 20 epochs and a learning rate of 0.0001 achieved the best performance, yielding an accuracy and F1-score of 0.97 and successfully fulfilling the objective of developing a reliable detection system that addresses the limitations of conventional manual feature extraction. The deployment of this model within a Flask-based web application further strengthens the practical contribution of the research by providing an accessible tool that can assist farmers in performing rapid and accurate disease identification. However, the study is limited by its use of laboratory-controlled image data, which may not fully represent real field conditions. Therefore, future work should include real-world testing and the integration of additional supporting technologies to enhance model robustness and support broader implementation within precision agriculture practices in Indonesia.

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