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Classification of Corn Leaf Disease Detection Using ResNet50 and Inception V3

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A B S T R A C T

Corn is an important food crop in Indonesia, requiring accurate classification methods to support agricultural productivity. To evaluate and compare ResNet50 and Inception V3 models with augmentation techniques for corn image classification. Deep learning classification using CNN architectures with rotation, shifting, and flipping augmentation. 3,560 corn images (2,500 training, 700 validation, and 360 testing). ResNet50 achieved 93.05% accuracy, while Inception V3 achieved the highest performance with 94.02% accuracy, 93.04% precision, 93.00% recall, and 93.02% F1-score. Image augmentation significantly improved classification performance, and Inception V3 was identified as the most effective model for corn image classification.

1. Introduction

Corn is a vital food crop and ranks among the most widely cultivated cereal crops globally [1]. A sustainable corn industry plays a critical role in ensuring global food security and advancing agricultural sustainability [2]. Data form Central Statistics Agency (BPS), indicate that corn production declined by approximately 12.50% from 16.62 million tons in 2022 to 14.46 million tons in 2023 [3]. This reduction underscores the necessity for improved crop management and enchanced disease monitoring strategies to sustain corn productivity. Figure 1 shows the decline in corn production in Indonesia during 2022–2023, indicating the importance of implementing effective disease detection and prevention strategies in agricultural practices [4].

One of the causes of the decline in the quality and quantity of corn harvests is because corn plants are very susceptible to disease and pests [5]. In corn plants, there are several main types of diseases that attack leaves, namely leaf blight, leaf spots, leaf rust and leaf blight [5], [6]. Among these types of diseases, leaf blight is a disease that has the potential to reduce corn production by up to 50% which is caused by Bipolasris Maydis [7]. To detect diseases in corn leaves can be done manually through human vision by looking at changes in color in corn leaves, but this takes a long time because it has to be identified in large quantities [8]. In addition, manual diagnosis is highly dependent on human expertise and is prone to inconsistencies. Therefore, an automatic disease detection system that is fast, accurate, and efficient is needed to support precision agriculture and improve crop management.

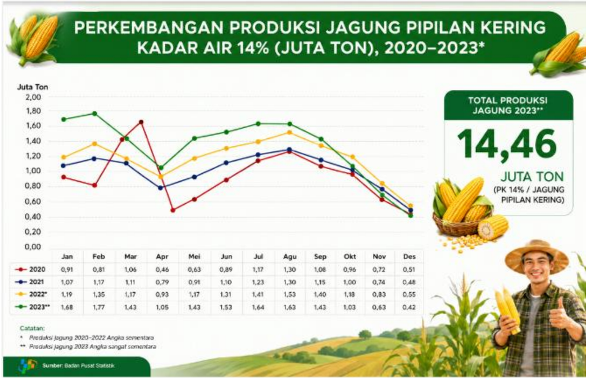

Figure 1. Development of Corn Production, Water Content

Recent advances in artificial intelligence, particularly in deep learning, have made big strides in detecting plant diseases. Many research studies have used techniques based on convolution neural networks (CNN) to detect diseases in corn leaves. Several studies have successfully applied CNN-based architectures for corn leaf disease classification, as summarized in Table 1.

Table 1. Related Research on Corn Leaf Disease Detection

Researcher	Algorithm	Dataset	Object	Accuracy
Afifi et al., 2021 [2]	ResNet18, ResNet34, ResNet50, Triplet networks, Deep Adversarial Metrics Learning)	PlantVillage	Corn Leaves	Up to 78%
Mishra and Banerjee, 2020 [9]	Self-trained CNN model	PlantVillage	Corn Leaves	88.66%
Garg and Rani, 2021 [10]	Mask R-CNN	Data Primer	Corn Leaves	91%
Sibiya dan Sumbwanyambe, 2019 [11]	Self-trained CNN model	PlantVillage	Corn Leaves	92.85%
Amin et al., 2022 [12]	CNN, Deep Learning, Deep Features, Feature Fusin	Field images + PlantVillage database	Corn Leaves	98.37%
Syarief and Setiawan, 2020 [4]	AlexNet VGG16, VGG19, GoogleNet, Inception-V3, ResNet50, ResNet101	PlantVillage	Corn Leaves	93.5%

Previous studies have reported promising classification performance using various deep learning architectures for corn leaf disease detection. Afifi et al. [2] evaluated several transfer learning models, including ResNet18, ResNet34, and ResNet50, and achieved an accuracy of up to 78%. Mishra and Banerjee [9] proposed a self-trained CNN model that achieved 88.66% accuracy on the PlantVillage dataset. Garg and Rani [10] employed Mask R-CNN and reported an accuracy of 91%. Similarly, Sibiya and Sumbwanyambe [11] reported an accuracy of 92.85% using a CNN-based model trained on the PlantVillage dataset. Furthermore, Amin et al. [12] combined deep learning with feature fusion techniques and achieved the highest reported accuracy of 98.37% using both field images and the PlantVillage dataset. In addition, Syarief and Setiawan [4] compared several transfer learning architectures, including AlexNet, VGG16, VGG19, GoogLeNet, InceptionV3, ResNet50, and ResNet101, and reported that transfer learning models achieved an average accuracy of 93.5% for corn leaf disease classification.

Although previous studies have demonstrated promising performance in corn leaf disease classification, several limitations remain, including limited dataset diversity, complex preprocessing requirements, and reduced generalization under real field conditions. The self-trained CNN model still has overfitting issues because tha training data is not enough and not very varied.

The preprocessing step is already complex as in the Multichannel CNN model, which can hinder practical applications, as it requires significant time and resources. In addition, there are several models that do not consider variations in real conditions in the field, poor model performance on field images indicates the need for representative data. Some model architectures, such as ResNet and Mask R-CNN, have specific limitations such as low accuracy on certain data and the curse of dimensionality. These limitations indicate the need for the development of more efficient and accurate deep learning models. In this study, ResNet50 and InceptionV3 were employed as transfer learning models and fine-tuned using a local corn leaf disease dataset. The proposed approach utilizes data aygmentation techniques, including rotation, shifting, and dlipping, to enrich the training data and improbe model robustness. Fine tuning allows the pre-trained models to extract discriminative features specific too corn leaf disease, resulting in improved classification accuracy and better generazation across diverse image conditons [4], [11], [13], [14].

Therefore, this study employs ResNet50 and InceptionV3 as transfer learning models and fine-tunes them using a local corn leaf disease dataset enhanced through data augmentation techniques. The proposed approach is intended to improve model robustness and generalization under diverse image conditions while reducing the need for complex preprocessing. The findings of this study are expected to contribute to the development of a practical and reliable deep learning approach for automated corn leaf disease classification in real agricultural environments.

2. Research Method

This study proposes a deep learning-based framework for corn leaf disease classification using transfer learning with ResNet50 and InceptionV3 models. To improve model generalization and address class imbalance, data augmentation techniques including rotation, shifting, and flipping were applied before model training. The overall research workflow is presented in Figure 2.

2.1. Collecting Data

The dataset used in this study uses plant village and also datasets obtained from previous research on corn leaves (Balijetsro) obtained from previous studies [15]. This data is mainly in the form of images of corn leaves infected with disease and healthy ones with each level of severity (mild, moderate and severe). Researchers ensure that the data collected covers various conditions and levels of disease severity to ensure the diversity and completeness of the dataset that will be used in the study from the disease data that has been collected only complete datasets other than that are not complete. Representative samples of the dataset are shown in Figure 3.

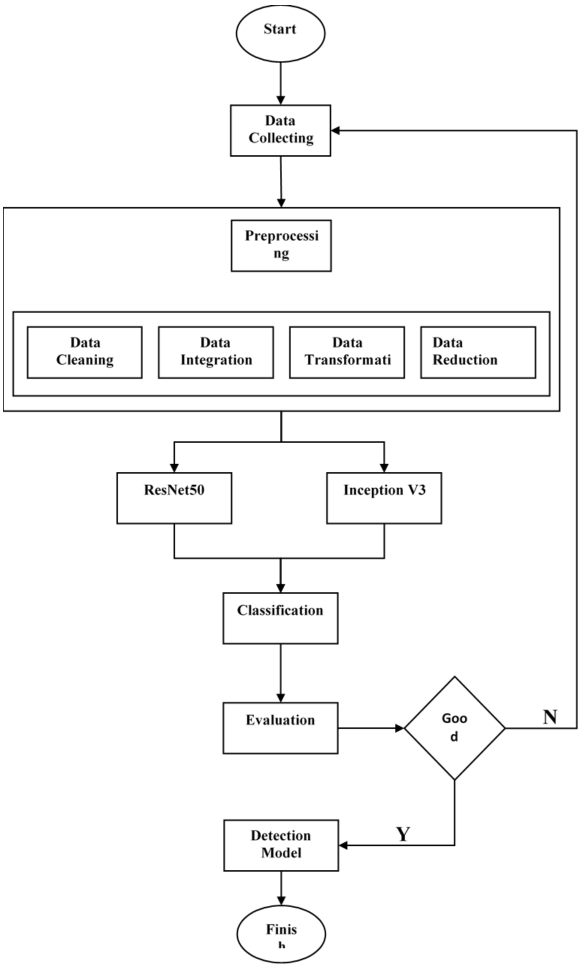

Figure 2. Stages of Research on Corn Leaf Disease Detection

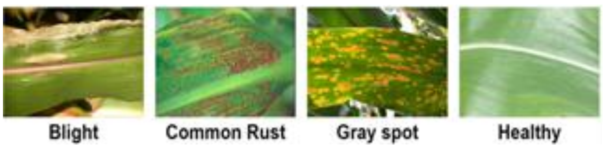

Figure 3. Corn Leaf Disease

Figure 3 provides a visual image for detecting and classifying the severity of corn leaf disease which can be used for research or development of deep learning-based detection models. Blight shows symptoms of blight with the presence of elongated spots parallel to the leaf veins. Common rust disease is seen on the leaves as having small brownish red spots and usually spreads on the leaf surface which can reduce the leaf's ability to carry out photosynthesis effectively. Gray Spot is characterized by small, rectangular to oval shaped spots and is healthy showing fresh green corn leaves without any signs of infection or damage.

2.2. Preprocessing Data

The dataset used in this study for the experimental is called the corn leaf disease dataset, and it includes a total of 2184 images. All the images in the dataset are in RGB format. The dataset includes these diseases: gray leaf spot, common rust, corn leaf blight, and healthy corn leaves. Each image is 224 pixels wide, 224 pixels tall, and has 3 color channels. At this stage it is important to ensure clean and representative data before training the model. The data distribution scheme plan uses 70:20:10 (Training, Testing, Validation), if the results of this experiment are not good, a further scheme will be tried to get better results.

2.3. Model Architecture

The Resnet 50 model was trained and adjusted using the data that had already been prepared. The process of fine-tuning means changing the setting of a model that has already learned a lot from a big set of data, so it can work better at identifying and grouping different types of diseases on corn leaves. This model was selected because its design allows it to understand and recognize detailed features in leaf images [16].

Inception V3 Model the Inception V3 model was also trained and fine-tuned using the same data. This process was carried out in parallel with the Resnet 50 training. Inception V3 is known for its ability to handle variations in scale and orientation in images, thus providing a different perspective in detecting diseases [17]. The two transfer learning models were trained and evaluated independently to compare their classification performance and identify the most suitable architecture for corn leaf disease classification.

2.4. Classification

The combined feature set is used to train the classification model. The deep learning model used for classification aims to detect and measure the severity of corn leaf disease. This model is expected to be able to provide accurate predictions based on the features provided.

2.5. Evaluation

The trained classification model is evaluated at this stage to assess its performance. Evaluation is carried out using performance metrics such as accuracy, precision, recall, and F1-score to ensure the model works well. If the model is not good, another experimental scheme will be carried out if the results are good, they will be used as recommendations for the disease severity prediction model, especially in corn leaves. Here are some formulas for implementing research:

2.5.1. Model Accuracy

Accuracy measures the correct proportion of overall predictions made by the model [18].

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

This accuracy can be calculated by comparing the predicted severity level with the actual severity level of the corn leaf image

2.5.2. Precision

Precision is used to measure the accuracy of the positive predictions made by the model [10]. Precision is calculated for each disease class. Especially if there are several levels of severity.

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

True positives (TP) is the number of cases where the model detects the correct disease severity.

False Positives (FP) is the number of cases where the model incorrectly detects a disease in a leaf that is not actually present.

2.5.3. Recall (Sensitivity or Recall)

Recall measures how well the model can find positive cases (or how well the model recognizes each disease severity class) [19].

$$Recall = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Negatives\ (FN)} \quad (3)$$

False Negatives (FN) is the number of cases where the model fails to detect the correct disease or severity.

2.5.4. F1-Score

F1- score is the harmonic mean of precision and recall [15]. F1-score is useful when there is an imbalance between the number of positive and negative cases.

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

A sample implementation of the proposed transfer learning model is presented below. The code illustrates the implementation of the deep learning architecture using TensorFlow and Keras, including feature extraction, classification layers, and model construction for corn leaf disease classification.

Sample of algorithm

```
import tensorflow as tf

from tensorflow.keras.applications import
ResNet50, InceptionV3

from tensorflow.keras.layers import Dense,
Dropout, GlobalAveragePooling2D, Concatenate

from tensorflow.keras.models import Model

# Input layer

input_shape = (224, 224, 3)

input_tensor =
tf.keras.Input(shape=input_shape)

# ResNet50

resnet_base = ResNet50(weights='imagenet',
include_top=False, input_tensor=input_tensor)

resnet_output =
GlobalAveragePooling2D()(resnet_base.output)

# InceptionV3

inception_base =
InceptionV3(weights='imagenet',
include_top=False, input_tensor=input_tensor)

inception_output =
GlobalAveragePooling2D()(inception_base.outpu
t)

# Gabungkan fitur

combined_features =
Concatenate()([resnet_output,
inception_output])

# Fully connected layers

x = Dense(512,
activation='relu')(combined_features)

x = Dropout(0.5)(x)

output = Dense(len(label_map),
activation='softmax')(x)

# Final model

model = Model(inputs=input_tensor,
outputs=output)

 # Summary

model.summary()
```

3. Result and Discussion

This section presents the experimental results of the proposed deep learning models for corn leaf disease classification. The discussion begins with the description of the dataset preparation and augmentation process, followed by the comparative performance evaluation of the ResNet50 and InceptionV3 models. Furthermore, the best-performing model is further analyzed using the confusion matrix, while the learning behavior of both transfer learning models is evaluated through their training and validation accuracy and loss curves. These analyses provide a comprehensive assessment of the effectiveness of the proposed approach for corn leaf disease detection.

Table 2. Dataset Splitting Results

Split	Healthy	Blight	Common Rust	Gray Spot	Total
Training	700	600	500	300	2500
Validation	200	150	140	100	700
Testing Process	100	80	70	50	360

Table 2 presents the distribution of the dataset after the augmentation process. Initially, the dataset contained 2,184 corn leaf images belonging to four classes, healthy, blight, common rust, and gray spot. Since the original dataset exhibited class imbalance, data augmentation techniques including rotation, shifting, and flipping were applied to increase the number of samples and improve model generalization. As a result, the dataset size increased from 2,184 to 3,560 images. The augmented dataset was subsequently divided into 2,500 images for training, 700 images for validation, and 360 images for testing. The augmentation process not only increased the dataset size but also enchanced class representation, thereby reducing the risk of overfitting and improving classification performance. Overall the data set is balanced across classes, allowing for a robust training, validation and testing process, this can ensure the model has enough data to generalize well when tested under various conditions.

Table 3. Performance Comparison of ResNet50 and InceptionV3

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ResNet50	93.05	92.08	91.05	92.01
InceptionV3	94.02	93.04	93.00	93.02

Table 3 presents a comparative analysis of the ResNet50 and InceptionV3 models for corn leaf disease classification. The experimental result show than InceptionV3 achived the highest performance with an accuracy of 94.02%, precision of 93.04%, recall of 93.00%, and F1-score of 93.02%, outperforming ResNet50, which obtained an accuracy of 93.05%, precision of 92.08%, recall of 91.05%, and F1-score of 92.01%. These findings are consistent with previous studies that demonstrated the effectiveness of deep learning architectures in plant disease classification.

For example, Mohanty et al. reported that deep convolutional neural networks achieved accuracy exceeding 99% on the PlantVillage dataset under controlled condition [14]. Similarly, ferentions achived classification accuracie ranging from 95% to 99% using CNN-based models across multiple crop species. Furthermore, Too et al. compared several transfer learning models and found than Inception-based architectures consistently demonstrated superior feature extraction capabilities for plat disease recognition tasks [20].

Compared with these studies, the performance obtained in this research is slightly lower, which may be attributed to the greater variablility of real-world corn leaf images, including differences in lighting conditions, leaf orientations, disease severity levels, and background complexity. Nevertheless, the achieved accuracy of 94.02% demonstrates that the proposed augmentation strategy combined with InceptionV3 provides robust classification performance for corn leaf disease detection.

Overall, the results indicate that both ResNet50 and InceptionV3 are effective for corn disease classification; however, InceptionV3 exbitits bettes generalization capability and superior performance acress all evaluation metrics, making it a more suitables model for practical agricultural disease monitoring applications.

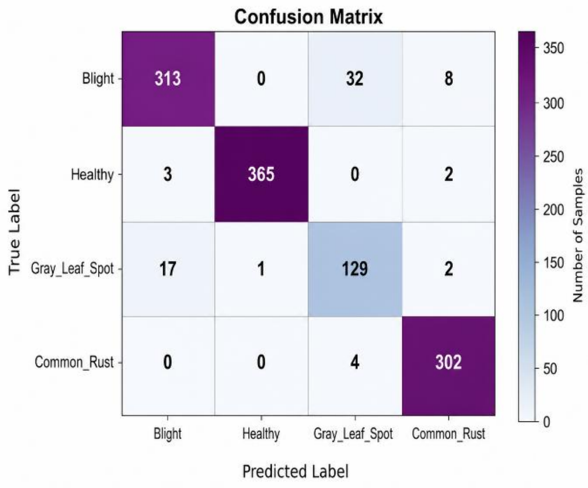

Figure 4. Confusion Matrix of the InceptionV3 Model

Figure 4 provides a detailed class-level evaluation of the best-performing InceptionV3 model by illustrating the distribution of correct and incorrect predictions for each disease category. While Table 3 summarizes the overall performance metrics, the confusion matrix reveals the classification behavior for individual classes. The Healthy class achieved the highest classification performance, with 365 correctly classified samples and only 5 misclassifications. The Common Rust class also demonstrated excellent performance, with 302 correct predictions and only 4 misclassified samples. In contrast, the Blight class recorded 313 correct predictions but exhibited the largest number of misclassifications, primarily confused with Gray Leaf Spot. Similarly, Gray Leaf Spot achieved 129 correct predictions, with most errors occurring when samples were predicted as Blight. This confusion is likely caused by the visual similarity between the symptoms of these two diseases, particularly in lesion color, texture, and shape. Overall, the confusion matrix confirms the robustness of the InceptionV3 model while highlighting the remaining challenges in distinguishing visually similar disease classes.

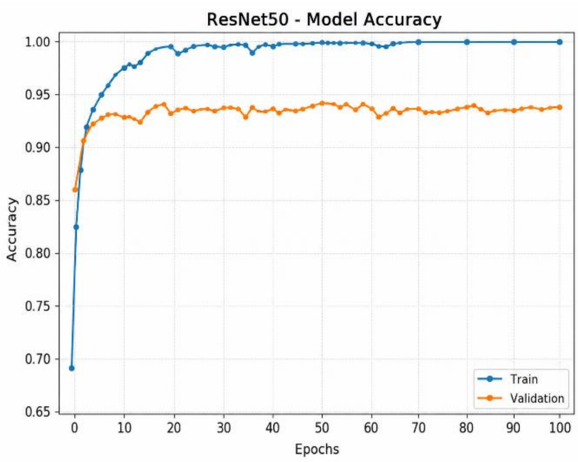

Figure 5. Training and Validation Accuracy of the ResNet50 Model

Figure 5 illustrates the training and validation accuracy curves of the ResNet50 model during the training process. The training accuracy increased rapidly and approached 100%, indicating that the model effectively learned the training samples. In contrast, the validation accuracy stabilized at approximately 93–94% after the early epochs, demonstrating consistent performance on unseen validation data. The gap between the training and validation curves suggests a slight tendency toward overfitting; however, the stable validation accuracy indicates that the model maintained good generalization capability. These observations are consistent with the final testing accuracy of 93.05% reported in Table 3.

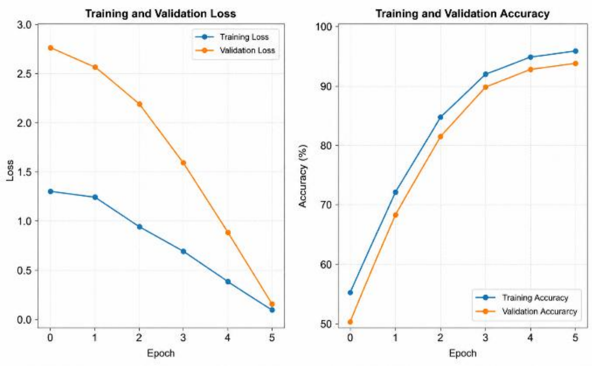

Figure 6. Training and Validation Accuracy and Loss Curves of the InceptionV3 Model

Figure 6 illustrates the training and validation accuracy and loss curves of the InceptionV3 model throughout the training process. The training and validation accuracy increased steadily with each epoch, reaching approximately 94%, respectively, at the final epoch. At the same time, both training and validation loss decreased consistently, indicating that the model progressively learned discriminative features while reducing classification errors. The relatively small gap between the training and validation curves suggests that the model generalized well to unseen data without exhibiting significant overfitting. Overall, these results demonstrate that the proposed training strategy enabled the InceptionV3 model to achieve stable convergence and robust classification performance for corn leaf disease detection.

4. Conclusion

This study proposed and evaluated two transfer learning models, ResNet50 and InceptionV3, for corn leaf disease classification using data augmentation techniques. Experimental results demonstrated that InceptionV3 outperformed ResNet50, achieving an accuracy of 94.02%, precision of 93.04%, recall of 93.00%, and F1-score of 93.02%. The confusion matrix further confirmed that the proposed model accurately classified most disease categories, with only minor confusion between Blight and Gray Leaf Spot due to their similar visual characteristics. In addition, the training and validation curves indicated stable convergence and good generalization capability, demonstrating the effectiveness of the proposed approach for automated corn leaf disease detection. Future work should evaluate larger field datasets and investigate additional disease categories under real agricultural conditions.

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