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Identifying Corn Leaf Diseases Using CNN Algorithm

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Abstract

Diseases in maize plants are one of the main factors contributing to yield reduction, ultimately impacting food security and the sustainability of the agricultural sector. Technological advancements have enabled digital image processing to become a widely applied method in various fields, including object identification, pattern detection, and plant disease classification with the support of Artificial Intelligence (AI). This study utilizes maize leaf images as a dataset, which is then processed using the Convolutional Neural Network (CNN) method based on the ResNet-50 architecture. This architecture is known for its superior ability to extract deep visual features, thereby enhancing classification accuracy. The CNN model operates by identifying and analyzing key features in images, such as color, texture, and damage patterns on maize leaves, to detect the type of disease affecting the plants. The methodology in this research involves several crucial stages, starting from collecting maize leaf image datasets directly from agricultural fields, preprocessing data to improve image quality for optimal model training, and finally, training and evaluating the CNN model's performance. The initial dataset consisted of 1,199 images, which, after image analysis, was reduced to 870 for processing. These were then split into 552 images for training, 87 for testing, and 261 for validation. The CNN model evaluation with 87 test images showed that the highest precision was achieved in the Rust Disease class (100%). Meanwhile, the highest recall was found in the Normal Leaf class (99%), indicating that the model correctly identified all normal leaf samples. However, the recall for the Fall Armyworm Disease class was 89%. This model accurately identifies damage patterns, making it a potential tool for automatic early disease detection in plants. Thus, this research can serve as a foundation for further developments in AI-based applications to enhance efficiency and accuracy in plant disease diagnosis, ultimately supporting agricultural productivity and sustainable food security.

Keywords:
Deep Learning, CNN, ResNet-50, Maize Leaf Disease Detection, Artificial Intelligence, Computer Vision.

1. Introduction

Artificial Intelligence (AI) is an advanced technology that enables computers to perform various tasks that were previously only possible for humans. One of these tasks is disease identification through image analysis with a very high level of accuracy. The primary goal of AI is to replicate human intellectual capabilities in solving problems efficiently and promptly [1]. With advancements in digital image processing technology, previous studies have explored the use of various features, such as color, texture, and fractal dimensions, as indicators in the classification process of plant leaves [2].

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One of the main branches of AI that is highly relevant in image analysis is Deep Learning, which employs the Convolutional Neural Network (CNN) method. CNN has been proven highly effective in identifying visual patterns in images, making it a valuable tool in various fields, including agriculture. The primary objective of using CNN in plant image analysis is to improve efficiency and accuracy in automatically detecting and classifying plant diseases [3]. The CNN method utilizes multiple convolutional layers to analyze patterns and visual characteristics in plant images, enabling disease classification with higher accuracy than manual methods. This, in turn, helps farmers take faster and more precise actions to maintain agricultural productivity [4].

Since CNN has been widely applied in image analysis for various needs, including plant disease identification, it offers higher accuracy than methods such as Multi-Layer Perceptrons (MLP) due to its complex network architecture, which allows for more thorough object evaluation [5]. However, the main challenges in using CNN for plant disease detection include the similarity of symptoms among diseases and the influence of environmental factors. CNN overcomes these challenges through techniques such as data augmentation, which increases image variations, and Transfer Learning, which enables models to leverage knowledge from pre-trained datasets [6]. Previous studies have shown that the CNN method can achieve a classification accuracy of up to 97.5% in identifying corn leaf diseases. Additionally, CNN has been extensively used in classification research, where it can identify plant characteristics based on shape and color with a success rate of 98.75% [7]. Further studies also confirm that CNN can reach up to 97.5% classification accuracy in detecting corn leaf diseases [8].

Moreover, CNN has been applied in detecting various corn plant diseases, such as gray leaf spot (Cercospora), common rust, and northern leaf blight, with accuracy exceeding 90% [9]. Another study revealed that CNN achieved an accuracy of 99.66% in detecting apple plant diseases, and 95-99% accuracy in distinguishing between healthy and infected leaves [10]. One of the most effective techniques for improving accuracy is using deeper and more complex network architectures, such as Squeeze And Excitation-Based Densely Connected CNN (SEDCNN), which has demonstrated optimal performance in identifying plant diseases with an accuracy of 97% [11]. Additionally, a custom Lightweight CNN (LCNN) model showed superior performance with 99% accuracy in training and validation and 95% in testing. Meanwhile, InceptionV3 achieved 96% training accuracy, 98% validation accuracy, and 92% testing accuracy, whereas CNN-DFE had 86% training accuracy, 94% validation accuracy, and 82% testing accuracy [12].

Furthermore, research has developed cloud-based applications and machine learning systems for automatically detecting plant diseases, allowing CNN to help reduce diagnostic thresholds while improving detection speed and accuracy compared to manual observations [13]. A CNN-based software application has also been developed for other purposes, such as real-time flower species identification with 96% accuracy and object detection using deep learning, making it highly suitable for plant disease classification [14].

Based on the explanations above, this research will employ the Convolutional Neural Network (CNN) algorithm to accurately detect corn leaf diseases. This approach will assist users in identifying and implementing appropriate treatment measures for corn plant diseases. This study aims to develop a corn leaf disease detection system using the CNN method in a practical application and to evaluate the effectiveness of the CNN model in detecting corn leaf diseases within an application. Afterward, this study also assesses the impact of data reduction on CNN performance in detecting corn leaf diseases.

2. Proposed Method

This study adopts a systematic approach by utilizing the ResNet-50 architecture to achieve optimal and efficient results. This strategy ensures that every crucial element in the research is thoroughly analyzed and appropriately integrated.

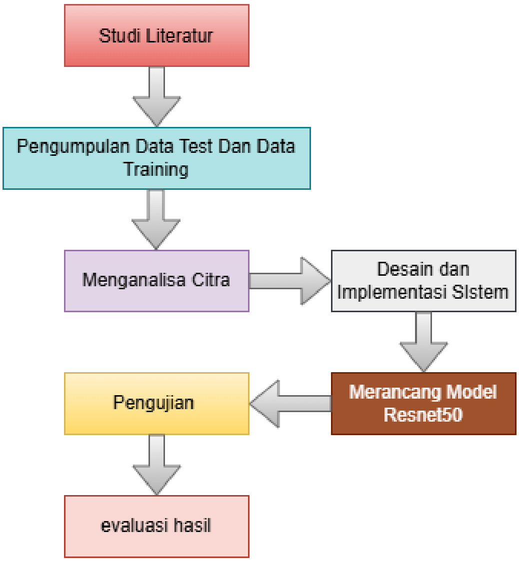

Fig 1. Research Framework Diagram

The researcher evaluates the performance of the Convolutional Neural Network (CNN) model in classifying diseases in corn leaves using the Confusion Matrix as the evaluation metric. The Confusion Matrix is used to analyze the model's accuracy by comparing the predicted results with the actual labels. This metric measures the number of correct and incorrect predictions in the categories of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Based on this analysis, the Confusion Matrix in this study is formulated as follows.

Table 1. Confusion Matrix

Actual Data	Classification Result	
	+	-
+	TP	TN
-	FP	FN

Accuracy $$= \frac{TP+TN}{TP+TN+FP+FN} x100\% \quad (1)$$

Precision $$= \frac{TP}{TP+FP} x100\% \quad (2)$$

Recall $$= \frac{TP}{TP+FN} x100\% \quad (3)$$

Specificity $$= \frac{TN}{TN+FP} x100\% \quad (4)$$

This study begins with an in-depth literature review on the application of the Convolutional Neural Network (CNN) method in classifying diseases in corn leaves. Various books and scientific journals related to CNN research and the ResNet-50 architecture are examined. In the next stage, data is collected in the form of corn leaf images obtained directly from the Department of Agriculture. The dataset is divided into two categories: testing data and training data. The initial dataset consists of 1,199 images, which undergo an image analysis process, resulting in 870 images for processing. The data is then split into 552 for training, 87 for testing, and 261 for validation. The dataset is classified into three categories: Normal leaves (Normal), Common Rust (Puccinia sorghi) dan Armyworm infestation (Armyworm**).**

Table 2. Experimental Dataset

No	Label	Picture
1	Normal Leaf	
2	Leaf Rust (*Puccinia sorghi)*	
3.	*Armyworm*	

The test data presented in this study consists of three types of findings, including one disease, one pest infestation, and one healthy corn leaf**.** Healthy corn leaves have a fresh and bright green color**,** a regular leaf pattern**,** and no spots or damage on the leaf surface. Yellow spots on the leaf surface and orange or brown pustules are characteristic signs of rust disease**.** These insect larvae are active both during the day and at night. They often chew through or create holes in the leaves, causing significant damage, including yellowing and curling of leaves, stunted plant growth, and in severe cases, dwarfing of the crop.

An analysis of corn leaf images is conducted to identify specific features that distinguish healthy leaves from infected ones, enabling the system to classify diseases with higher accuracy and efficiency. Additionally, pooling operations are applied to reduce the data dimensions during the convolution process through down-sampling techniques, aiming to improve processing efficiency without losing essential information in feature extraction [15].

This design phase focuses on developing the software required to guide the system and identify key components necessary for data processing. This process ensures that research objectives are achieved more effectively and systematically. Furthermore, this stage includes designing a detailed description of the features, capabilities, and technical characteristics of the electronic devices or computers used. In this study, the proposed model utilizes transfer learning with ResNet-50. Transfer learning aims to enhance task performance by transferring knowledge learned from a source task to a target task**.** Residual Network (ResNet-50) is an architecture within CNN**,** designed to address the vanishing gradient problem in deep learning networks. The ResNet model has undergone various testing and refinements to improve effectiveness in feature learning [16].

The testing phase involves testing the model developed in the previous stages. The model is evaluated using different images to determine whether it performs well in classifying corn leaf diseases**.** The results from testing, including performance metrics and error analysis**,** must be reported. This ensures that the model is reliable and that its findings can be understood by relevant stakeholders, such as farmers or researchers**.**

3. Result and Analysis

At this stage, an analysis and model design will be conducted on the data. The steps to be carried out are shown in Fig 2**.**

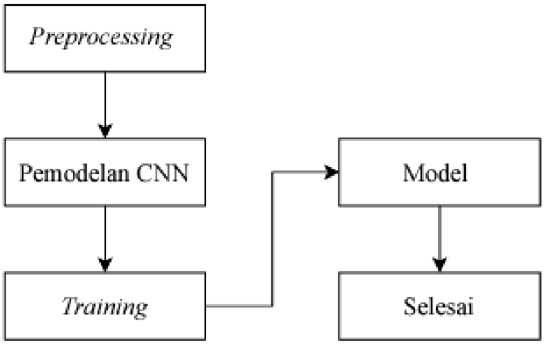

Fig 2. Flowchart of the CNN Algorithm Process

At the initial stage, where the training and test data are imported into three classes. The Data clusters are presented in Table 3.

Table 3. Dataset Cluster Table of Corn Leaf Plants

No	Folder	Train	Validation	Test
1.	Leaf Rust	313	56	45
2.	Armyworm	330	94	47
3.	Normal Leaf	196	56	28

In this study, we conduct Augmentation to generate new training data from the original dataset and input it with a pixel size of 224 x 224. Afterward, the model development process utilizes a Transfer Learning approach to assist in feature extraction, aiming to use a more optimal model. The feature extraction method employed in this study is the Residual Network Layer (ResNet50), as shown in Fig 3.

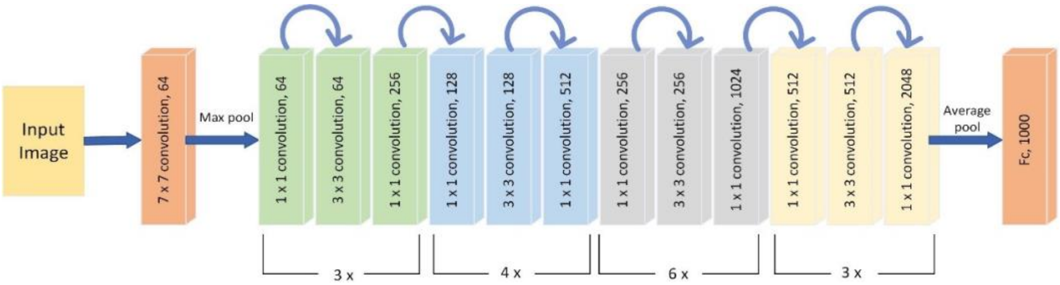

Fig 3. Filter Size and Channels in ResNet50

This study undergoes the training process as a crucial step that involves using training data to build the model and comparing it with validation data. The primary goal of this process is to generate images that can accurately identify the types of diseases and pests on corn leaves, in line with the research focus. Before running the training, several parameter configurations must be set, as listed in Table 4.

Table 4. Parameter Size

Hyper-parameter	Filter
Batch size	32
Epoch	15
Optimizer	Adm
Learning rate	0.001

Batch size refers to the number of data samples processed simultaneously in one iteration during CNN training [17]. Meanwhile, an epoch represents a complete cycle in which the entire dataset is used to train the model before restarting for the next iteration. The Adam optimization algorithm is used to improve the accuracy of the developed model by adaptively adjusting the learning rate [18]. Adam itself is a gradient-based optimization method that combines the advantages of momentum and RMSProp to accelerate convergence and enhance the stability of the CNN training process [19]. The training results can be seen in Tables 5 and Tables 6.

Table 5. Training Results of Train Data

Epoch	Loss Train	Accuracy Train
1	0.96	0.80
2	0.47	0.89
3	0.72	0.88
4	0.42	0.89
5	0.34	0.89
6	0.46	0.87
7	0.71	0.85
8	0.91	0.86
9	0.68	0.88
10	0.51	0.88
11	0.65	0.87
12	0.34	0.92
13	0.60	0.89
14	0.41	0.87
15	0.32	0.91

Table 6. Training Results of Validation Data

Epoch	Loss Validation	Accuracy Validation
1	1.45	0.84
2	0.48	0.91

3	2.76	0.92
4	0.73	0.97
5	2.43	0.89
6	1.34	0.96
7	0.80	0.86
8	1.53	0.78
9	0.21	0.95
10	2.46	0.95
11	16.68	0.54
12	10.59	0.70
13	0.69	0.95
14	0.14	0.97
15	0.04	0.98

Training accuracy is used to assess the model's accuracy on the data used during the training process. Meanwhile, validation accuracy measures the model's performance on previously unseen data, which is separate from the training data, to evaluate the model's generalization ability. The accuracy results obtained in this study are illustrated in Fig 4.

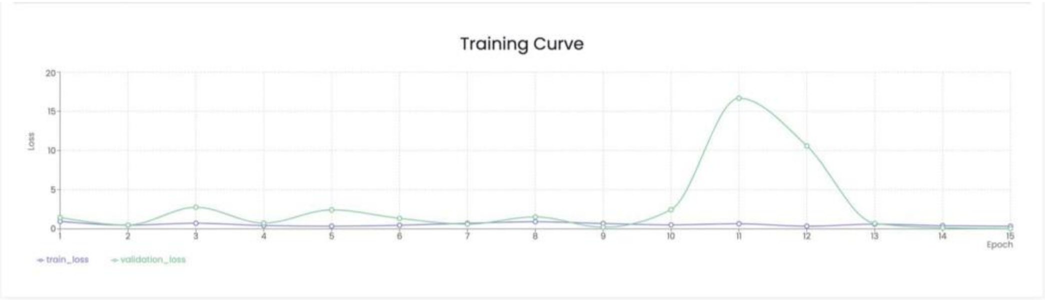

Fig 4. Training and Validation Graph

After training, a trained model is generated and saved in **.h5** format and will be used for classification with new data that is not included in the training or validation data.

4. Conclusion

The findings of this study demonstrate that the Convolutional Neural Network (CNN) method, particularly when enhanced with transfer learning using the ResNet50 architecture, is highly effective in classifying image-based data, even with a constrained dataset. The model achieved a training accuracy of 91% and a validation accuracy of 98%, indicating strong generalization capability. While CNNs are inherently powerful for image analysis, their performance is typically dependent on large-scale datasets for optimal training. The success of transfer learning in this context highlights its utility in mitigating data limitations, enabling robust classification without extensive custom training data. Furthermore, the application of CNN-based transfer learning not only improves classification accuracy but also enhances data quality assessment, contributing to operational efficiency in production environments. However, future research should explore the model's adaptability to more diverse and complex datasets, as well as its resilience against adversarial perturbations. These advancements could further solidify the role of deep learning in automated quality control and predictive maintenance systems.

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