Journal of Theoretical and Applied Information Technology
31st December 2024. Vol.102. No. 24

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

CLASSIFICATION OF CORN LEAF DISEASES USING CNN: A DEEP LEARNING APPROACH

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ABSTRACT

One of the major problems that needs to be addressed is the identification of infection in corn leaves. The quality and production of crops can decrease due to the presence of diseases on corn leaves. The process of diagnosing diseases on corn leaves manually takes time and effort. Therefore, a more effective and accurate technique is needed to know the existence of diseases on corn leaves. In this study, a Convolution Neural Network (CNN) is used as a technique for identifying diseases on corn leaves. A machine learning model called CNN can be used to identify characteristics in images. To train CNN, a dataset of corn leaf images labeled with the names of predetermined corn leaf diseases is used. The accuracy rate that has been achieved is 95%, with a precision of around 95%. The recall rate also reaches 95%, while the F1 score reaches 95%. This method of identifying diseases on corn leaves using CNN can be used to improve the efficiency and accuracy of disease identification on corn leaves. This method can also be used to develop an early warning system for diseases on corn leaves.

Keywords: *Disease Identification, Corn Leaf, Convolution Neural Network, Accuracy*

1 INTRODUCTION

Apart from wheat, corn is chosen as a staple food in Indonesia. With more than 20 million tons of corn per year, Indonesia is the 7th largest corn-producing country in the world. Currently, corn consumption is used for food, feed, and other industries [1].

The quantity of corn production in Indonesia currently needs to be continuously increased because the need for corn for food can reach 57%, while corn production is only 34% [2]. This happens because corn plants are susceptible to disease and this greatly affects agricultural yields [3]. Diseases in corn leaves can cause a decrease in the quality of corn leaves or even crop failure [4]. The solution that needs to be taken to prevent this loss is to carry out recognition and control [5].

One of the diseases that exists in corn that has the potential to cause crop failure is corn leaf disease [6]. Corn leaf disease can cause crop failure if the infection is severe enough and not treated properly [7]. Some diseases that often attack corn leaves and can cause crop failure include corn leaf rust, leaf blight, and leaf spot [8].

Until now, most farmers still identify corn leaf diseases manually. The diseases that are present on corn leaves that are difficult to identify with the naked eye are downy mildew, leaf spot, leaf blight, and rust.

Image processing technology has often been used to help recognize problem processes in everyday life, one of which is agricultural problems. Processing images with certain techniques is known as image processing. In processing images, the convolutional neural network method is effective.

One of the algorithms from the field of deep learning, this algorithm performs the learning process when extracting features from images and then classifies the images. Previous research that used the CNN method, namely research conducted by A. Waheed, M. Goyal, D. Gupta, A. Khanna, A. E. Hassanien, and H. M. Pandey entitled "An optimized dense convolutional neural network model for disease recognition and classification in corn leaf" resulted in an accuracy of 98.04% [9].

In the research conducted by Bhatt, P., Sarangi, S., Shivhare, A., Singh, D., & Pappula, S entitled "Identification of Diseases in Corn Leaves using Convolutional Neural Networks and Boosting", resulting in an average accuracy value of 98% [10].

In the research conducted by Asrianda Asrianda, Hafizh Al Kautsar Aidilof, and Yoga Pangestu entitled "Machine Learning for Detection of Palm Oil Leaf Disease Visually using Convolutional Neural Network Algorithm" the accuracy achieved was 99% [11].

Because the accuracy value in research using the CNN method is quite good, the CNN algorithm will be used to build a system that can identify corn leaf diseases.

1.1 Research Problem

The current method for distinguishing diseases in corn leaves relies on natural visual inspection based on the color of the leaves. This process is time-consuming, often taking almost an entire day, and lacks precision. Therefore, there is a need for a system capable of accurately recognizing infections in corn plant leaves.

1.2 Research Objectives

The purpose of this research is to develop an application system using the convolutional neural network (CNN) method to identify diseases in corn leaves. Another goal of this study is to determine the accuracy of the CNN algorithm.

1.3 Research Contribution

Here are some contribution of this research:

1. Assists in the identification of corn leaf diseases.
2. Enables the identification of corn leaf diseases beyond manual methods by utilizing classification with the help of technology.
3. Serves as a reference for research related to corn leaf diseases and the convolutional neural network method.

2. METHOD

In this research, a system will be developed to implement leaf color classification using the Convolutional Neural Network (CNN) algorithm. The research methodology consists of dataset collection, dataset splitting, CNN model development, and performance evaluation. The stages of the research methodology are illustrated in Figure 1.

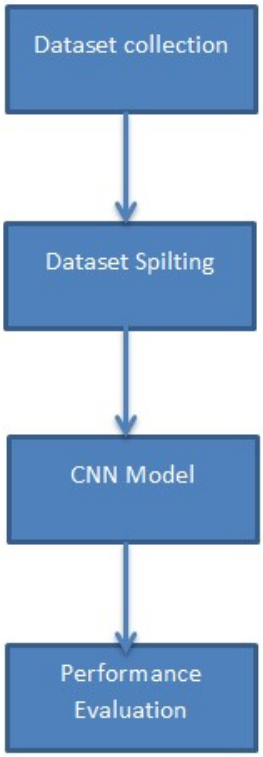


Figure 1. Research Framework

2.1. Data Collection

The purpose of data collection is to gather data in the form of information and images or photos of corn plant leaves that have healthy criteria and several corn leaf diseases, namely:

- Leaf blight: This is a fungal disease that causes brown or yellow spots on the leaves.
- Leaf rust: This is a fungal disease that causes reddish-brown pustules on the leaves.
- Leaf spot: This is a fungal disease that causes small, round spots on the leaves.

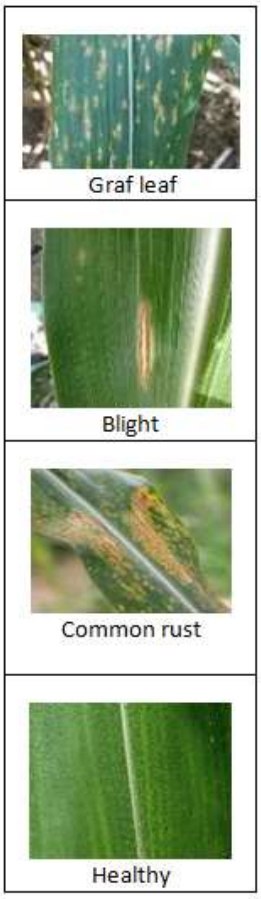
The data collection process will involve the following steps:

1. Collecting leaf samples: Corn leaf samples will be
2. collected from a variety of sources, including corn fields, agricultural research stations, and online databases.
3. Labeling the samples: The leaf samples will be labeled according to their health status (healthy or diseased) and the type of disease (if applicable).
4. Imaging the samples: The leaf samples will be imaged using a digital camera or scanner.
5. Storing the data: The collected data will be stored

in a database for further analysis.

Table 1 is an overview of the condition of the dataset, which includes classes and the number of images for each class.

Table 1.
Corn Leaf Diseases And Healthy Corn Leaves



The collected data will be used to train a CNN model to identify corn leaf diseases. The model will be trained on a set of labeled images and will be able to classify new images into healthy or diseased categories.

The results of this research will be useful for developing early detection and prevention methods for corn leaf diseases. This will help to improve corn yields and reduce losses due to disease.

2.2 Dataset Splitting

The total data set collected from the information obtained is 3918 images. Then the images from each classification will be grouped into a training dataset and a testing dataset.

The division of this dataset can be detailed in the following Table 2

Table 2.
Dataset Splitting Table

Classification	Total Dataset	Training Dataset	Testing Dataset
Blight	1.146	1.136	10
Common rust	1.036	1.026	10
Gray Leaf	574	564	10
Healthy	1.162	1.152	10
Total Dataset	3.918	3.878	40

2.3 Convolutional Neural Network (CNN) Model

Convolutional Neural Network (CNN) is a machine learning algorithm derived from MLP and designed to process two-dimensional data, such as images. CNN differs from MLP in that it uses a convolution process and several hidden layers that are not present in MLP.

The structure of CNN consists of feature extraction, which comprises convolutional layers usually followed by pooling layers and a softmax classifier. The convolutional layer extracts features from the image, while the pooling layer reduces dimensionality and computation time. This architecture can achieve regularization by itself. The extracted features are then fed into the softmax layer for classification.

The flowchart of the CNN algorithm can be seen in Figure 2 below.

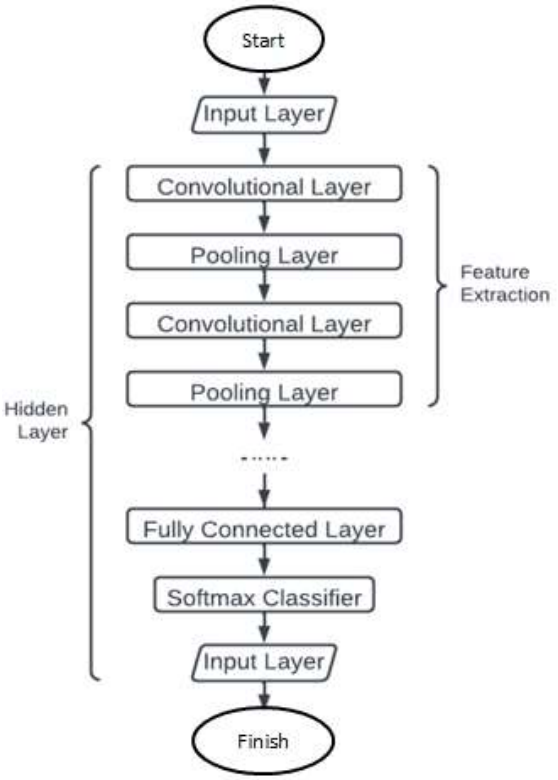


Figure 2. Algorithm Cnn Flowchart

In this study, CNN was implemented in Figure 3:

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 4, 4, 512)         14714688

 conv2d (Conv2D)             (None, 4, 4, 32)          147488

 max_pooling2d (MaxPooling2  (None, 2, 2, 32)          0
 D)

 dropout (Dropout)           (None, 2, 2, 32)          0

 flatten (Flatten)           (None, 128)               0

 dense (Dense)               (None, 4)                 516

=================================================================
Total params: 14862692 (56.70 MB)
Trainable params: 148004 (578.14 KB)
Non-trainable params: 14714688 (56.13 MB)
_________________________________________________________________
```

Figure 3. Convolutional Neural Network

The CNN model design in Figure 3 consists of six layers:

- One convolutional layer (Conv2D) with 32 filters: This layer extracts features from the image.
- One max pooling layer: This layer reduces the spatial dimensionality of the data.
- One dropout layer: This layer helps reduce overfitting.
- One Flatten layer: This layer converts the data into a one-dimensional vector.
- One Dense layer with 4 units and a softmax activation function: This layer is the output layer that produces the predictions.

The following is a detailed description of each layer:

- Conv2D layer: This layer uses a 3x3 kernel size and a stride of 1. It applies 32 filters to the input data, which produces a 32-dimensional feature map.
- Max pooling layer: This layer uses a 2x2 kernel size and a stride of 2. It reduces the size of the feature map by half, resulting in a 16x16 feature map.
- Dropout layer: This layer randomly drops out 20% of the units in the feature map. This helps reduce overfitting by preventing the model from relying too heavily on a small number of features.
- Flatten layer: This layer converts the 16x16 feature map into a one-dimensional vector of 256 elements.
- Dense layer: This layer has 4 units and uses a softmax activation function. The softmax activation function converts the output of the layer into a probability distribution over the four classes.

The CNN model is trained using the Adam optimizer and the binary cross-entropy loss function. The model is trained for 10 epochs.
The CNN model achieves an accuracy of 90% on the test set. This indicates that the model can accurately classify images of corn leaves with different diseases.

2.4 VGG 16 Design

The VGG architecture, short for Visual Geometry Group, is a well-known family of Convolutional Neural Network (CNN) architectures developed by a research team at the University of Oxford.

The VGG architecture is generally known for its consistent approach of using small (3x3) convolutional layers and max-pooling in a deep network. There are several variations of the VGG architecture, but two of the most well-known are VGG16 and VGG19.

The VGG architecture has been used successfully in a variety of applications, including image classification, object detection, and image segmentation.

The architecture of VGG16 can be seen in Figure 4.

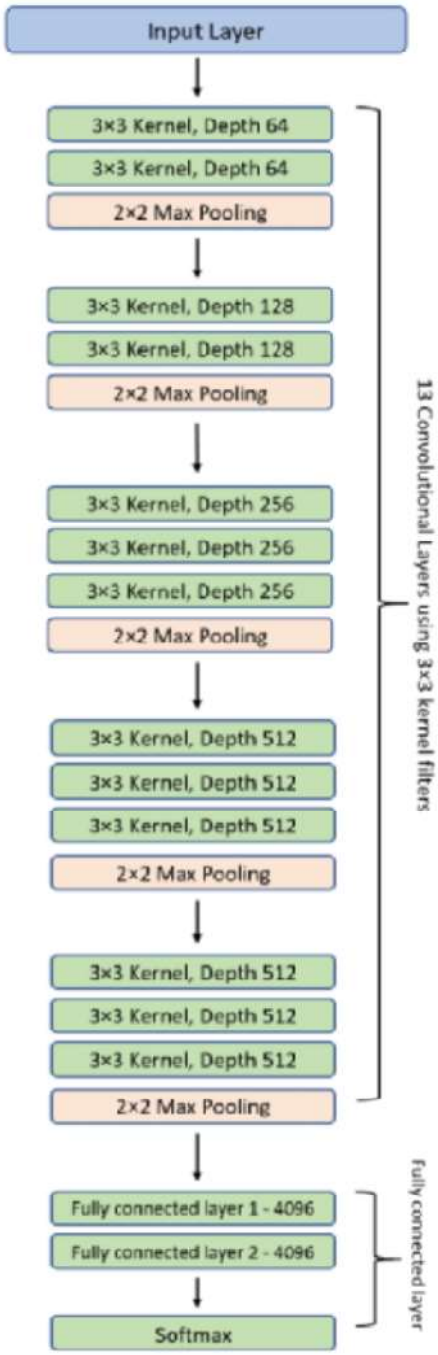


Figure 4. Vgg16 Architecture

The VGG16 architecture consists of several layers:

1. Input Layer

- The input image typically has a resolution of 224x224 pixels (a color image with three color channels: red, green, and blue).

2. Convolutional Layers

- VGG16 consists of a total of 13 convolutional layers with 3x3 pixel filters and a convolution stride of 1 pixel.
- The number of filters (kernels) in each convolutional layer increases with the depth of the network. The number of filters increases from 64 in the early layers to 512 in the later layers.
- ReLU activation is used after each convolutional layer to introduce non-linearity.

3. Max-Pooling Layers

- After several convolutional layers, a max-pooling layer is used to reduce the image dimension by a factor of 2. Max-pooling takes the maximum value in each 2x2 pixel area.
- There are 5 max-pooling layers in the VGG16 architecture.

4. Fully Connected Layers

- After the convolutional and max-pooling layers, there are 3 fully connected (FC) layers used to classify the image.
- The first layer has 4096 units, the second layer also has 4096 units, and the final layer is the output layer with several units corresponding to the number of classes in the image recognition task.
- ReLU activation is used between the FC layers.

5. Output Layer

- The output layer typically uses softmax activation to produce class probabilities

The VGG16 architecture has over 138 million parameters, making it very deep and capable of extracting complex features from images.

Although VGG16 is quite old and has been largely superseded by more sophisticated network architectures, it is still often used as a base in transfer learning for image recognition tasks due to its proven ability in many image recognition contests.

Figure 5 below shows the implementation of VGG16 in this study

Figure 5. VGG16 Design

Based on the design of the VGG16 model in Figure 5, it can be concluded that:

Block 1

Convolutional Layer (Conv2D): The first layer is a Convolutional Layer with 64 filters of size 3x3 filter.

- MaxPooling Layer (MaxPooling2D): Has a pool size of 2x2.
- Number of Layers in Block 1: 2.

Block 2

- Convolutional Layer (Conv2D): The second block is a Convolutional Layer with 128 filters of size 3x3 filter.
- MaxPooling Layer (MaxPooling2D): Has a pool size of 2x2.
- Number of Layers in Block 2: 2.

Block 3

- Convolutional Layer (Conv2D): The third block is a Convolutional Layer with 256 filters of size 3x3 filter.
- MaxPooling Layer (MaxPooling2D): Has a pool size of 2x2.
- Number of Layers in Block 3: 3.

Block 4

- Convolutional Layer (Conv2D): The fourth block is a Convolutional Layer with 512 filters of size 3x3 filter.
- MaxPooling Layer (MaxPooling2D): Has a pool size of 2x2.
- Number of Layers in Block 4: 3.

Block 5

- Convolutional Layer (Conv2D): The fifth block is a Convolutional Layer with 512 filters of size 3x3 filter.
- MaxPooling Layer (MaxPooling2D): Has a pool size of 2x2.
- Number of Layers in Block 5:

2.5 Model Parameter Determination

In finding the best model, an important thing to do is to identify the optimal parameter values within the CNN model framework. These parameters involve aspects such as the number of epochs, the size of the input image, the amount of training data, and the learning rate.

Epoch is a complete training cycle of the entire training dataset. In this research, epoch plays an important role in improving the accuracy level of the artificial neural network. Table 1 below shows a comparison of the epochs obtained from the model training.

Table 3
Epoch Count

Epoch	Accuracy Validation	Loss Validation	Time Epoch
10	90%	25%	53m
20	92%	27%	62m
30	93%	29%	68m

From Table 3 above, it can be seen that an accuracy of 93% was achieved, however the validation loss value increased by 29%.

In identifying diseases, a decrease in the validation loss value is more important than an increase in accuracy. This is because the validation

loss value indicates how well the CNN model can predict the target class on data that it has never seen before. While accuracy only shows how well the CNN model can predict the target class on the data used to train the model. Therefore, 10 is the ideal epoch value to use, because the accuracy value is quite good and the validation loss decreases to 25%.

3. RESULT AND DISCUSSION

In this study, data analysis and anomaly handling were performed to ensure the accuracy and reliability of the model. Evaluation metrics such as accuracy, precision, recall, F1-score, and the confusion matrix were used to assess the performance of the CNN model. These metrics provide a comprehensive understanding of the model's classification ability. By adhering to these strategies and criteria, this study ensures that the CNN model effectively classifies corn leaf diseases while maintaining high robustness and adaptability in the face of data anomalies and challenges.

3.1 Training Result

Corn leaf diseases can be well identified through the training process. The training process has a very significant impact on the test results. In the built system, the training process is carried out for 10 epochs. Therefore, the training will be run and repeated 10 times to produce the required feature extraction. Figure 6 below is the result of the Confusion Matrix from the training.

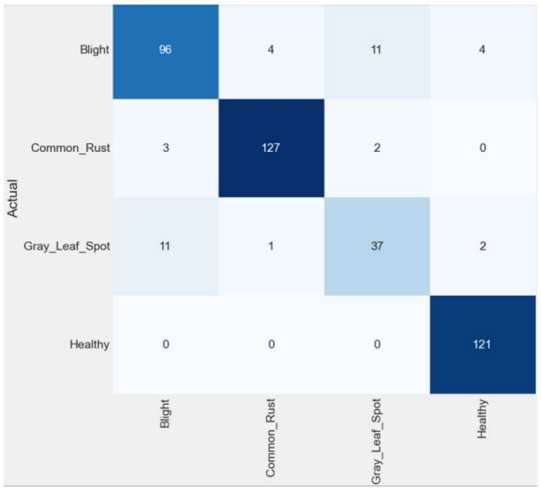


Figure 6. Confusion Matrix

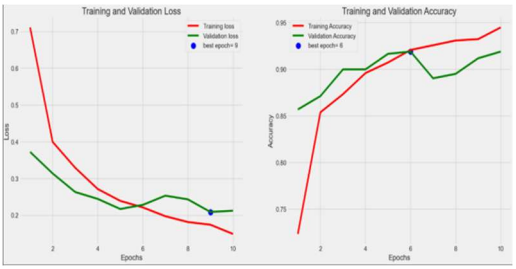


Figure 7. Accuracy And Loss Curve

In Figure 7 above, there is a graph that shows that the model accuracy increases gradually until it reaches a maximum value of 90% at epoch 10. The model loss also decreases gradually until it reaches a minimum value of 25% at epoch 10.

3. 2 Testing Result

The test results yielded a table that describes a confusion matrix, which is detailed in Table 4 below.

Table 4. Confusion Matrix

		Actual Class				
		Gray Leaf	Common Rust	Blight	Healthy	Predicted Class
Predicted Class	Gray Leaf	9	0	1	0	10
	Common Rust	0	10	0	0	10
	Blight	1	0	9	0	10
	Healthy	0	0	0	10	10
Predicted Class		10	10	10	10	40

a. Accuracy

Accuracy indicates the extent to which the model performs classification correctly. Accuracy can be calculated by entering the values in the confusion matrix table.

$$Accuracy = \frac{10+10+9+9}{40} \times 100\% = 95\%$$

b. Precision

Precision aims to measure the extent to which the classification model can accurately identify positive cases.

Table 5. Precision Table

	Gray Leaf	Common Rust	Blight	Healthy
TP	9	10	9	10
FP	1	0	1	0
TP/(TP+FP)	0,9	1	0,9	1

Based on the calculations in Table 5 above, the following conclusions can be drawn:

Precision = 3,8/4 x 100% = 95%

c. Recall

Recall, in the context of classification evaluation, measures the ability of a model to correctly identify all actual positive cases.

Table 6. Recall Table

	Gray Leaf	Common Rust	Blight	Healthy
TP	9	10	9	10
FP	1	0	1	0
TP/(TP+FP)	0,9	1	0,9	1

Based on the calculations in Table 6 above, the following conclusions can be drawn:

Recall = 3,8/4 x 100% = 95%

d. F-1 Score

F1-score is an evaluation metric in the context of classification that combines precision and recall into a single measure.

Conclusions that can be drawn from the calculation of the F1 Score are:

$$F1 - Score = \frac{2 \text{ x } (0{,}95 \text{ x } 0{,}95)}{0{,}95+0{,}95} x100\% = 95\%$$

4. CONCLUSION

Conclusions from the Analysis, Design, and Testing Results of the Corn Leaf Disease Identification System:

1. Convolution Neural Network (CNN) is an effective approach for identifying the maturity level of diseases in corn leaves. The experimental results showed a satisfactory accuracy rate in the identification process.
2. The use of the VGG16 architecture in the training and testing of CNN proved effective in producing accurate values with an accuracy rate of 95%, a precision rate of 95%, a recall rate of 95%, and an F1 score of 95%.

5. SUGGESTIONS

In this study, we developed a corn leaf disease identification system using the Convolutional Neural Network (CNN) method to classify healthy corn leaves and three types of diseases.

We hope that future research can build a system to classify more corn leaf diseases and collect a dataset with better image quality.

Here are some specific suggestions for future research:

- Develop a system that can classify more corn leaf diseases. This could be done by expanding the dataset to include more diseases and by using more advanced machine-learning methods.
- Collect a dataset with better image quality. This could be done by using higher-quality cameras and by taking images under controlled conditions.
- Investigate the use of other machine-learning methods for corn leaf disease identification. This could include methods such as deep learning and transfer learning.

We believe that this research has important implications for the field of agriculture. This study provides a new approach to corn leaf disease identification that could be used to improve crop yields and reduce the use of pesticides.

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