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# Identification of Staple Crops Diseases in Indonesia Using Convolutional Neural Network

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**ABSTRACT:** In Indonesia, rice stands as the primary staple food, derived from the rice plant, alongside cassava and corn. The successful cultivation of these crops significantly impacts the nation's food security. Consequently, a program was initiated to facilitate disease detection in these plants, aiming to optimize harvest yields. One prevalent challenge in disease identification is discerning their distinctive features. With technological advancements, disease recognition can now be automated using information technology, particularly neural networks. This study employed the Convolutional Neural Network (CNN) method with Inception v3 architecture to diagnose diseases in staple crops. Furthermore, the model was converted using TensorFlow Lite for integration into Android-based smartphone applications. The research program successfully identified diseases in corn, potato, cassava, and rice plants, achieving an average accuracy rate of 86.35% through conducted experiments.

**KEYWORDS:** disease identification, staple crops, convolutional neural networks, inception v3.

## I. INTRODUCTION

Nutrition constitutes a fundamental necessity in human life, essential for daily sustenance. Within Indonesia, rice stands as the predominant staple, boasting the highest consumption rates globally. Moreover, corn consumption within the nation surpasses that of many other countries [1]. Additionally, cassava and sweet potatoes complement the dietary landscape. Cassava, a local carbohydrate source, ranks third in Indonesia's staple hierarchy, following rice and corn [2]. Furthermore, potatoes emerge as another staple option. Globally, potatoes claim the fourth position among essential food crops, trailing rice, wheat, and corn [3]. These four staples assume a pivotal role in meeting human carbohydrate requirements, serving as primary sources of energy for daily activities.

The prosperity of crop yields from these essential plants can significantly impact a nation's agricultural sector. However, crop failures remain a constant threat, often attributable to diseases and pest infestations. According to a survey conducted in 2012, nearly 40% of global harvests are lost annually due to such issues [4]. Indonesia also confronts similar challenges. For instance, in Sukarena village, Tiga Dihaji district, South Ogan Komering Ulu (OKU) regency, farmers endured substantial losses, with approximately 14 hectares of rice fields decimated by unfamiliar pests, leaving them reliant solely on local government aid [5]. Similarly, in West Manggarai regency, farmers faced a crisis as they abandoned cocoa plantations, an economic lifeline for the community, due to an unidentified disease ravaging the crops, leaving them perplexed and without recourse [6].

Detection of diseases and pest invasions typically involves scrutinizing different plant components, including leaves, stems, and fruits. Leaves are often the most accessible part for detection, as disease symptoms are frequently evident. Nevertheless, disease identification poses a challenge for non-experts, demanding specialized knowledge. In an effort to streamline disease recognition for the wider populace, in this paper, we concentrate on developing an application with the capacity to identify diverse diseases afflicting staple crops.

## II. RELATED WORK

Until now, several studies have been conducted on the recognition of plant leaf diseases. One of them is the recognition of diseases on banana leaves conducted by Amara et al. [7]. This study used Convolutional Neural Network (CNN) with LeNet architecture and also tested whether color information affects the accuracy of disease recognition. The dataset used was preprocessed and resized to 60 x 60 pixels with RGB (Red, Green, Blue) and

grayscale colors before being inputted into the model. The accuracy obtained averaged 97.31% and proved that color information provides higher accuracy than grayscale. In 2018, Tm et al. also conducted a similar study on tomato plants using CNN with LeNet architecture [8]. The images obtained were also resized to 60 x 60 pixels, with the highest accuracy obtained being 94.52%.

Research on disease recognition on leaves was also conducted by Hossain et al. [9]. In this study, a different approach was taken, where images of five types of leaf diseases were collected, and RGB images were converted to Lab color space. The images were then segmented and converted into binary images. Feature extraction was performed, and the K-nearest neighbor method was used for classification. The accuracy obtained averaged 96.76% and proved that disease recognition could be achieved even with a small dataset.

In this paper, identification was conducted for the recognition of diseases in staple crops such as corn, potatoes, cassava, and rice using a neural network, particularly the CNN model with Inception v3 architecture. The CNN model has a deeper structure, resulting in less required training time and more flexible input sizes, while still maintaining accuracy levels comparable to other models.

### III. METHODOLOGY

The research methodology used in this study includes data collection, data partitioning and data processing, which will be explained in the subsections below. The data used in this research consists of RGB (Red, Green, Blue) color images of plant leaves in JPG (Joint Photographic Group) format.

#### 3.1 Data collection

The collected data comprises datasets of infected and healthy plant leaves. The plants studied include corn, potatoes, cassava, and rice. The dataset of plant leaves was obtained from three sources: 9148 images of corn plants and 7135 images of potato plants from PlantVillage [10], 9436 images of cassava plants from iCassava 2019 [11], and 3355 images of rice plants from the University of California Irvine [12]. This dataset will be used for training, validation, and testing to classify diseases in plant leaves. Figure 1 provides an example of the data to be used.



Fig. 1. Example of a Potato Plant Dataset

#### 3.2 Data partitioning

The obtained dataset is divided into 2 parts. The first part, consisting of 80% of the dataset, is used for training, while the second part, comprising 20%, is used for testing. In the PlantVillage dataset, maize plants are separated into 7316 images for training and 1832 images for testing, consisting of 1907 & 480 images of common rust disease, 1642 & 410 images of gray leaf spot disease, 1908 & 477 images of leaf blight disease, and 1859 & 465 images of healthy conditions. For potato plants, they are divided into 5702 images for training and 1433 images for testing, consisting of 1939 & 490 images of early blight disease, 1939 & 485 images of late blight disease, and 1824 & 458 images of healthy conditions.

In the iCassava 2019 dataset, cassava plants consist of 2422 images for training and 576 images for testing, consisting of 379 & 87 images of bacterial blight disease, 1162 & 281 images of brown streak disease, 626 & 147 images of green mite infestation, and 255 & 61 images of healthy conditions. In the University of California Irvine dataset, rice plants consist of 2684 images for training and 671 images for testing, consisting of 418 & 105 images of brown spot disease, 452 & 113 images of hispa infestation, 623 & 156 images of leaf blast disease, and 1191 & 297 images of healthy conditions.





### 3.3 Data processing

The collected dataset comes from various sources, resulting in images with different resolutions. Images with different resolutions need to be processed to a uniform size in terms of width and height. In the PlantVillage dataset, images of maize and potato plants already have the same resolution, which is 256 x 256 pixels for each image. However, in the datasets from iCassava 2019 and the University of California, images of plant leaves have different resolutions, requiring image resizing to a uniform size.

In addition to setting the image resolution, the dataset is also augmented to increase the limited dataset and reduce the likelihood of overfitting, which is one of the weaknesses of CNN models. In this research, positional errors in leaf image capture can have a significant impact. Therefore, geometric transformations are applied to the dataset to reduce this risk. Geometric transformation is an excellent solution for correcting positional biases in the training data. Some methods that can be applied include flipping, color space manipulation, cropping, rotation, translation, and noise injection. Augmentation experiments include flipping, color space manipulation, rotation, and translation is also used. This augmentation stage will be carried out using the Keras library.

Flipping, which entails flipping images horizontally and vertically, serves to benefit the model by accounting for potential variations in the angle at which leaves are captured by users. Manipulating the color space involves altering the RGB color channels of the image, such as eliminating one channel (red, green, or blue) or adjusting brightness, to aid in enhancing the model's ability to discern different weather conditions. Rotation involves rotating the image left or right by an angle ranging from 1 to 359 degrees, assisting the model in handling images captured from diverse angles by users. Translation entails shifting the image in various directions (left, right, up, or down), thereby mitigating positional bias in the dataset caused by users capturing images that are not perfectly aligned. Additionally, experiments involving zoom augmentation will be conducted, where images are zoomed in and out to help the model recognize images captured at varying distances. Following these experiments, the results will be combined to determine the most effective combination of augmentations.

## IV. EXPERIMENTAL RESULTS

Several experiments were conducted on the developed system utilizing a subset of the original dataset, precisely 20% of the total data. Additionally, experiments were conducted directly on plants infected with diseases sourced from the agricultural department. The evaluation of the neural network system involved tweaking parameters that could influence the model's performance. This experiment aimed to identify the optimal configuration for the CNN model to achieve peak performance.

To conduct evaluations on the testing data, a confusion matrix serves as the tool of choice. This matrix, utilized as a performance metric for classification models, comes in two variations: the 2-class confusion matrix and the multi-class confusion matrix. Performance assessment entails computing the values within the confusion matrix, typically encompassing four distinct combinations of predicted and actual values: True Positive (TP), where the predicted class aligns with the actual class; True Negative (TN), where the predicted class and actual class both indicate a negative outcome; False Positive (FP), where the predicted class is affirmative while the actual class is negative; and False Negative (FN), where the predicted class is negative despite the actual class being affirmative. Accuracy, defined as the proportion of correctly classified instances (TP and TN) to the total number of predictions, emerges as a crucial metric in this assessment process [13].

### 4.1 Preprocessing experiment

Utilizing the Keras library, image preprocessing is implemented to enhance the effectiveness of the Inception v3 model in image recognition tasks. This preprocessing phase entails standardizing the resolution of all images within the dataset and subsequently normalizing the pixel values of each image to fall within the range of -1 to 1. The purpose of this testing is to evaluate whether such preprocessing enhances the model's performance. Figure 2 illustrates an example showcasing the outcomes of the preprocessing stage.



Fig 2. Example of Preprocessing Results

The experiment was carried out on potato and cassava plant datasets, the parameters used were the Inception v3 architecture as a CNN model structure, the number of epochs was 10, and without data augmentation. The results of the preprocessing experiments can be seen in Table 1.

Table 1. Preprocessing Testing

| Plant                   | Lowest Accuracy | Highest Accuracy | Average Accuracy | Average Loss Function |
|-------------------------|-----------------|------------------|------------------|-----------------------|
| Potato (original)       | 88.9%           | 100%             | 98.72%           | 0.0425                |
| Potato (preprocessing)  | 99.03%          | 100%             | 99.87%           | 0.0033                |
| Cassava (original)      | 75.76%          | 87.05%           | 82.75%           | 0.6291                |
| Cassava (preprocessing) | 56.06%          | 90.38%           | 84.91%           | 0.5859                |

The experimental findings presented in Table 1 reveal that the original potato plant dataset exhibits the lowest accuracy level, inferior to the preprocessed dataset. Conversely, the highest accuracy remains consistent across datasets. Additionally, the potato plant dataset subjected to Keras preprocessing demonstrates a higher average accuracy and lower average loss function compared to the original dataset. Similarly, the original cassava plant dataset records the lowest accuracy, albeit surpassing the preprocessed cassava dataset. Nevertheless, the preprocessed cassava dataset achieves the highest accuracy, accompanied by superior average accuracy and reduced average loss function in comparison to the original dataset. These results underscore the efficacy of Keras preprocessing in enhancing the CNN model's performance.

#### 4.2 Augmentation Experiment

In this experiment, data augmentation was applied to the dataset as described in subsection 3.2. This experiment was conducted to assess whether the model can better recognize diseases when given augmentation or vice versa. The testing was performed on cassava plant dataset, utilizing the Inception v3 architecture as the CNN model structure, with 10 epochs, and without image preprocessing. Data augmentation testing involved combining a total of 5 types of augmentations: rotation, vertical translation, horizontal translation, flipping, and zoom. Combinations were made starting from 2, 3, 4, and 5 types of augmentations, and results were obtained for each combination including the lowest accuracy, highest accuracy, average accuracy, and average loss function.

From the experiments conducted, it was found that the best results for the combination of 4 types of augmentations were achieved with rotation, vertical translation, flipping, and zoom. The results of testing the combination of 4 types of augmentations can be seen in Table 2.

Table 2. Augmentation Testing

| Augmentation Type                                                   | Lowest Accuracy | Highest Accuracy | Average Accuracy | Average Loss Function |
|---------------------------------------------------------------------|-----------------|------------------|------------------|-----------------------|
| Original                                                            | 69.57%          | 84%              | 74.76%           | 0.7928                |
| Rotation + horizontal translation + vertical translation + flipping | 49.12%          | 83.44%           | 73.54%           | 0.9664                |

|                                                                 |        |        |        |        |
|-----------------------------------------------------------------|--------|--------|--------|--------|
| Rotation + horizontal translation + vertical translation + zoom | 69.1%  | 88.44% | 79.61% | 0.6980 |
| Rotation + horizontal translation + flipping + zoom             | 62.53% | 86.22% | 78.67% | 0.6924 |
| Rotation + vertical translation + flipping + zoom               | 72.16% | 89.07% | 85.59% | 0.5564 |
| Horizontal translation + vertical translation + flipping + zoom | 56.34% | 86.68% | 78.26% | 0.7773 |

From the augmentation experimental results, the best combination of augmentation types was found to be a combination of rotation, vertical translation, flipping and followed by zoom.

#### 4.3 Learning Rate Experiment

In learning rate testing, experiments are carried out using several types of learning rate parameters to find the best value for model training. This test was carried out using learning rates of 0.05, 0.03, 0.01, 0.005, 0.003, 0.001, 0.0005, 0.0003, and 0.0001 on the cassava plant dataset with 10 epoch parameters, without preprocessing and without augmentation. The results of this experiment can be seen in Table 3.

Table 3. Augmentation Testing

| Learning Rate | Lowest Accuracy | Highest Accuracy | Average Accuracy | Average Loss Function |
|---------------|-----------------|------------------|------------------|-----------------------|
| 0.05          | 5.64%           | 64.11%           | 42.46%           | 2.5522                |
| 0.03          | 8.79%           | 60.87%           | 37.86%           | 2.5544                |
| 0.01          | 20.07%          | 78.26%           | 52.29%           | 2.8315                |
| 0.005         | 19.24%          | 76.23%           | 57.97%           | 1.7366                |
| 0.003         | 12.49%          | 71.32%           | 50.30%           | 2.1689                |
| 0.001         | 39.04%          | 82.15%           | 62.02%           | 1.8694                |
| 0.0005        | 54.67%          | 84.55%           | 66.80%           | 1.1755                |
| 0.0003        | 60.87%          | 84.55%           | 73.58%           | 0.9016                |
| 0.0001        | 54.67%          | 84.55%           | 66.80%           | 1.1755                |

From the results of this experiment, the lowest and highest accuracy value was the learning rate of 0.0003, the highest accuracy was obtained by three values, namely 0.0005, 0.0003 and 0.0001. The highest average accuracy was obtained at a learning rate of 0.0003, and the lowest loss function value was also obtained at a learning rate of 0.0003. The results of this test show that the learning rate parameter value of 0.0003 provides the best performance for model training.

#### 4.4 Testing the Number of Epochs

In this experiment, several variations of the epoch parameters will be tested which will be used to find the number of epochs that provide the best performance. This experiment was carried out on a cassava plant dataset with a learning rate parameter of 0.0003, without preprocessing, and without data augmentation. The experimental result can be seen in Table 4.

Table 4. Epoch Testing

| Epoch | Training Accuracy | Training Loss | Testing Accuracy | Testing Loss |
|-------|-------------------|---------------|------------------|--------------|
| 10    | 98.11%            | 0.0586        | 83.72%           | 0.8632       |
| 15    | 98.28%            | 0.0512        | 80.39%           | 0.8810       |

|    |        |        |        |        |
|----|--------|--------|--------|--------|
| 20 | 98.52% | 0.0381 | 88.53% | 0.5148 |
| 25 | 97.72% | 0.0649 | 84.74% | 0.7030 |
| 30 | 99.48% | 0.0140 | 89.64% | 0.5697 |
| 35 | 97.81% | 0.0675 | 84.09% | 0.9212 |
| 40 | 99.56% | 0.0117 | 88.44% | 0.6132 |

The experimental results show that the highest testing accuracy value was obtained at the 30th epoch, namely 89.64% with a loss function value of 0.5697.

#### 4.5 Model Creation and Testing

After testing the neural network system and identifying the parameters that yield the best performance for the model, the model for each plant is created using these parameters and converted into Tensorflow Lite extension. Model creation is carried out for corn, potato, cassava, and rice plants. The models are built using a 3-channel color input layer (red, green, & blue). The datasets for each plant are first augmented and preprocessed. The parameters used for training the model include the Inception v3 architecture as the CNN model structure, 30 epochs, a batch size of 32, Adam optimizer, a learning rate of 0.0003, categorical cross-entropy as the loss function, and accuracy as the evaluation metric. The results of model testing of corn, potato, cassava and rice can be seen in Figure 3.

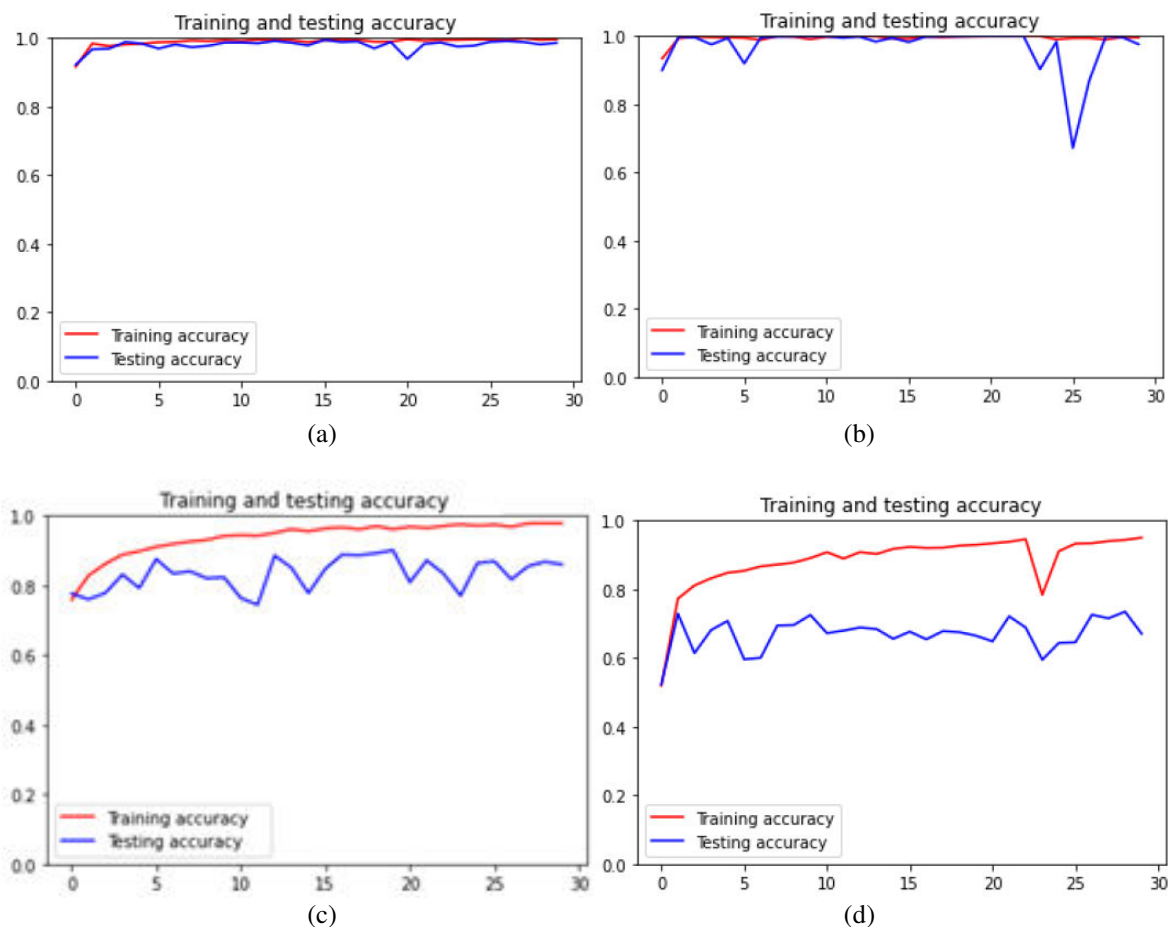


Fig 3. Training and Testing Result of (a) Corn (b) Potato (c) Cassava (d) Rice

Based on the test outcomes, it is evident that the average accuracy for corn plant testing stands at 97.92%. The most notable achievement was recorded during epoch 16, reaching an accuracy rate of 99.45%. During this epoch, the model

demonstrated precision, recall, and F1-score values of 99.02%, 98.78%, and 98.90% respectively. Conversely, in the case of potato plant testing, the average accuracy obtained is 97.10%. Particularly noteworthy are the results attained during epochs 20, 21, 22, and 23, where a perfect accuracy rate of 100.00% was achieved. Notably, during these epochs, the model exhibited precision, recall, and F1-score values of 100.00%.

During the evaluation of cassava plants, the average accuracy achieved stands at 83.34%, with the optimal result occurring at epoch 20, registering an accuracy rate of 90.19%. In this instance, the model attained a precision of 87.18%, recall of 87.83%, and F1-score of 87.25%. Subsequently, in the assessment of rice plants, an average accuracy of 67.04% was obtained. The highest accuracy in testing, recorded at epoch 29, reached 73.47%, accompanied by precision, recall, and F1-score values of 71.19%, 66.97%, and 68.27% respectively. Upon consolidating the outcomes of all tests, the average accuracy across all experiments culminates at 86.35%.

## V. CONCLUSION

In this research we developed a program to identify diseases in staple crops, namely corn, cassava, rice and potatoes. From the conducted tests, it can be concluded that the utilization of CNN method with Inception v3 architecture in plant disease recognition yields an average accuracy of 90.77% on the utilized dataset. Preprocessing with Keras and data augmentation successfully enhanced the model's performance. The best type of augmentation was found in the combination of rotation, vertical translation, flipping, and zoom. The optimal parameters obtained were using a learning rate of 0.0003 and a total of 30 epochs.

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