# Hyperparameter Optimization in CNN Algorithm for Chili Leaf Disease Classification

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Abstract: Diseases of a plant will greatly affect the yield. Chilli plants are one of the most frequently used food ingredients in various dishes in Indonesia. Leaves on chili plants are often affected by the disease, if the condition is not treated immediately, the disease can damage plants and result in crop failure, early detection of chili plant diseases is very important to do, to reduce the risk of crop failure. Technological developments and the application of deep learning algorithms can monitor chili plants automatically using a computer system. Using this algorithm, the system will analyze and identify diseases that can be seen and recorded by the camera. In this study, the proposed method uses the CNN algorithm by optimizing hyperparameters. The optimizers used are Adam, Nadam, SGD, RMSProp, and Adadelta with Epoch 50 and 100, Learning Rate 0.1, and Batch Size 8, 16, and 32. From the Optimizer used, the Nadam optimizer at epoch 100, batch size 16, learning rate 0.1 gives the most optimal results with 86% accuracy, 86% precision, 84% recall, and 84% f1-score. It is proven that the CNN algorithm and the Nadam architecture are well capable of classifying data according to its class.

## 1 INTRODUCTION

Indonesia is the fourth largest producer of chilli plants, nationally the chilli plants with the highest production rates (Zikra et al., 2021). Chilli plants are not a staple food crop, but become a complementary spice to Indonesian cuisine, with prices that are always fluctuating making chilli a contributor to inflation for the Indonesian economy (Rosalina and Wijaya, 2020), one of the things that make chilli a contributor to inflation because chilli prices often soar, and the causative factor is crop failure.

There are several factors that cause crop failure in chilli plants such as pests and diseases (L et al., 2018), pests and diseases become a serious threat to farmers because they can result in a decrease in the quality or quantity of the crop (Islam et al., 2020). In chilli plants, there are several types of pests and diseases that are often infected such as leaf curl, leaf spots, whitefly, and yellowish (Meilin and Tanaman Cabai Serta Pengendaliannya, 2014). Identifying the disease can be done by looking at the shape of the leaves and colour, but the shape of the leaves and the colour have similarities so it is difficult to do, especially for young farmers (Simalango et al., 2020). For this reason, it is necessary to handle early identification of types of pests and diseases, in order to reduce the risk of crop failure.

Deep learning is a computational model that is currently widely used in various fields, especially in agriculture (Saputra et al., 2022). There are several algorithms in the deep learning model, one of which is the Convolutional Neural Network (CNN) (Sekaran et al., 2020). The CNN algorithm has advantages compared to other algorithms (Anton et al., 2021), in the CNN algorithm there are Hyperparameters that we can optimize to get the maximum accuracy value (Gulcu and Kus, 2020). Hyperparameter is a network structure in the CNN algorithm that can be trained and optimized manually (Raziani and Azimbagirad, 2022; Zhu, 2018), Hyperparameter optimization in the CNN algorithm is a problem that many researchers and practitioners have found, to make hyperparameters more effective, experts need to determine some hyperparameters manually, the best results of this manual configuration are modelled and implemented on the CNN algorithm (Zhu, 2018).

In this paper, we propose a method to improve



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CNN performance by adjusting hyperparameters at the CNN feature extraction step. Research to detect chilli disease has been widely carried out such as research (Rozlan and Hanafi, 2022) using deep learning algorithms, namely CNN with the VGG16, InceptionV3, and EfficientNetB0 architectures, obtained InceptionV3 has the best accuracy of 98.83%. Research (Tsany and Dzaky, 2021) using CNN algorithms with AlexNet architecture, the accuracy of which is 90%. Research (Rosalina and Wijaya, 2020) used deep learning algorithms, with datasets collected personally, built applications and obtained an accuracy value of 68.8%. Research (Nuanmeesri and Sriurai, 2021) using the Multi-Layer Perceptron Neural Network (MLPNN) algorithm, obtained an accuracy value of 98.91%. Research (Sari et al., 2021) using SVM and GLCM algorithms, obtained an accuracy value of 88%. Research (Das et al., 2019) used machine learning with an accuracy result of 61.49%. Research (Zikra et al., 2021) using SVM and GLCM algorithms, the parameters used were three characteristics including contrast, correlation, and energy, while the characteristics using four which included contrast, correlation, energy, and homogeneity, obtained an accuracy rate of 95%. Research (Wahab et al., 2019) using the K-Means algorithm for Segmented and Support Vector Machine for classification, obtained accuracy results of 90.9% and Research (Muslim and Arnie, 2015) using the Bayes theorem algorithm in the application of the chilli pest and disease diagnosis expert system, obtained the results of pretest tests and posttests the accuracy results were 100%. Based on some of the research above, the research that will be carried out is to apply the CNN algorithm with the MobileNet architecture, and apply hyperparameter tuning to epoch, batch size, learning rate and optimizer (Adam, Nadam, SGD, RMSProp and Adadelta) during the Model training process. The model will be evaluated using a confusion matrix to see the level of accuracy, precision, recall and f1-score produced by the model.

## 2 METHODS

At this stage, explaining the stages of the method to be proposed, namely first collecting image datasets from data published on the Kaggle, the total data collected is 400 image images, consisting of 80 healthy images, 80 leaf curl images, 80 leaf spot images, 80 whitefly images, 80 yellowish images. Furthermore, the second stage is the preprocessing stage, at this stage, the image dataset is labelled consisting of five chilli leaf diseases, namely healthy, leaf curl, leaf spot, whitefly, and yellowish. Image data is divided into two parts, namely 80% training data and 20% testing data. In the third stage, we implemented the CNN model with MobileNet architecture with hyperparameter optimization, namely Epoch 50 and 100, Learning Rate 0.1, Batch Size 8, 16 and 32, with the Optimizer used, namely Adm, Nadam, SGD, RMSProp and Adadelta. And the last stage is to compare the accuracy, precision, recall and f1-score results of each Optimizer. Here's a picture of the proposed method:

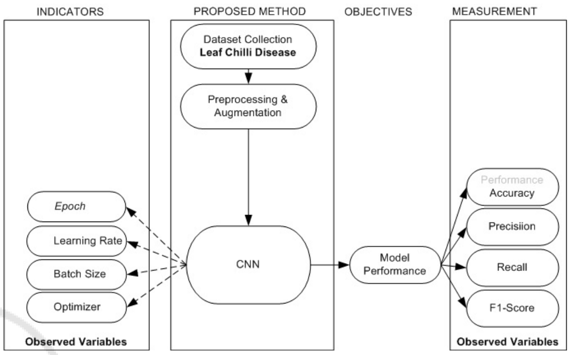


Figure 1: Proposed Methodology.

## 3 RESULT AND DISCUSSION

The experiment was conducted by training data training and data validation using the CNN MobileNetV2 architecture. In the training stage, the model will be carried out with several scenarios that aim to optimize the model in classifying chilli leaf disease. There were 4 optimization scenarios of the CNN model used in this study. The first scenario was tested on the number of epochs, the second scenario was tested for the influence of batch size, and the third scenario was tested for the influence of the optimal optimizer type, of the three scenarios using a learning rate of 0.1, with the aim of finding the best performance in each experiment. Furthermore, the model will be tested using training data consisting of 400 images of chilli leaf disease.

1. Influence Optimizer Testing
   The first scenario was tested on the use of epoch amounts 50 and 100 at the time of model training, this was done to find the number of epochs that

Table 1: Test Results With Epoch 50.

| Batch Size | 8 | | 16 | | 32 | |
|---|---|---|---|---|---|---|
| | Acc | Loss | Acc | Loss | Acc | Loss |
| Adam | 0.72 | 0.69 | 0.80 | 0.59 | 0.82 | 0.71 |
| Nadam | 0.82 | 0.54 | 0.80 | 0.54 | 0.80 | 0.55 |
| SGD | 0.82 | 0.51 | 0.80 | 0.55 | 0.78 | 90.47 |
| RMSProp | 0.80 | 0.56 | 0.82 | 0.45 | 0.70 | 1.39 |
| Adadelta | 0.24 | 1.82 | 0.18 | 1.89 | 0.24 | 1.83 |

had the best performance.

In the table above, it can be seen that from all types of optimizers tested, there is the same high accuracy result between optimizers, which is 0.82 even though the loss level is different, for that the RMSProp optimizer is the best because it has a small loss value compared to the other three optimizers.

Table 2: Test Results With Epoch 100.

| Batch Size | 8 | | 16 | | 32 | |
|---|---|---|---|---|---|---|
| | Acc | Loss | Acc | Loss | Acc | Loss |
| Adam | 0.80 | 0.48 | 0.80 | 0.57 | 0.82 | 0.48 |
| Nadam | 0.84 | 0.49 | 0.86 | 0.51 | 0.84 | 0.67 |
| SGD | 0.78 | 0.59 | 0.76 | 0.51 | 0.80 | 0.59 |
| RMSProp | 0.80 | 0.61 | 0.75 | 0.66 | 0.81 | 0.58 |
| Adadelta | 0.23 | 1.68 | 0.22 | 1.61 | 0.21 | 1.55 |

Based on Table 2 above, you can see the test results of various types of optimizers with an epoch of 100, and Nadam optimizers with batch size 16, resulting in the best accuracy value of 86% with the lowest loss value of 0.45. As for the SGD, Nadam RMSProp and Adadelta optimizers, the accuracy and loss values are not too different, but for the Adam optimizer, although it gets an accuracy of 82%, the performance is still below the Nadam optimizer tested. Graphs of accuracy and loss during CNN model training using the Nadam optimizer can be seen in Figure 2.

2. Model Evaluation
   To find out more about the performance of the CNN model used, an evaluation will be carried out using a confusion matrix in the training data (Gorunescu, 2011). The CNN model is evaluated to obtain accuracy, precision, recall and f1-score values. The results of the confusion matrix can be seen in Figure 3. Based on Figure 3 above, it was found that out of 80% of the images in the Healthy class, but there were 20% of the images were mispredicted, for the leaf curl class all images were successfully predicted correctly without any errors. In the leaf curl disease class, there is no correctly predicted imagery, in leaf spot imagery there is 90% of the image is predicted correctly while 10% is predicted incorrectly, while in whitefly imagery 100% is predicted correctly, and in yellowish imagery, 80% is predicted correctly and 20% is predicted incorrectly. From the results of the confusion matrix, accuracy, precision, recall, and f1-score values are obtained as seen in Table 3.

Table 3: Confusion Matrix Results.

| Accuracy | Precission | Recall | F1-Score |
|---|---|---|---|
| 86% | 86% | 84% | 84% |

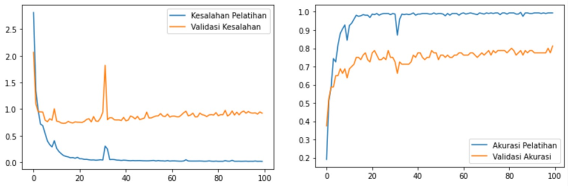


Figure 2: AUC Graph Optimzer Nadam With Epoch 100 and Batch Size 16.

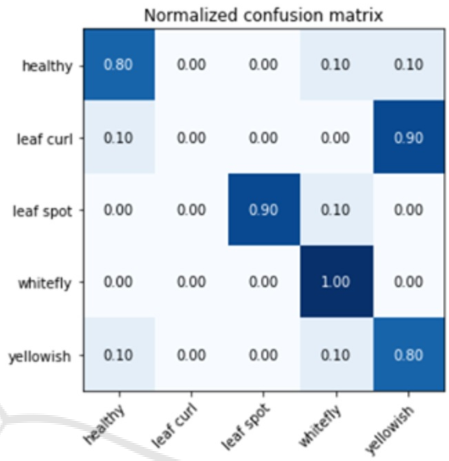


Figure 3: AUC Graph CNN Model With Optimzer Nadam and Epoch 100, and Batch Size 16.

Based on Table 3, it can be seen that the CNN MobileNet-V2 architecture used in this study by doing several hyper-parameter optimizations such as epoch, batch size, learning rate and optimizer can provide excellent results. This is proven from a series of experiments conducted so as to get an accuracy value of 86%, precision 86%, recall 84% and f1-score 84%.

# 4 CONCLUSIONS

This study optimized the CNN model using several hyperparameters such as epoch, batch size, learning rate and optimizers to classify rice diseases in Indonesia. The purpose of this study was to obtain optimal hyperparameters to achieve good performance on the CNN model. This study used CNN's MobileNet-V2 architecture as a training model. Based on the experiments that have been carried out, the determination of hyperparameters greatly affects the performance of the model. Hyperparameters with an epoch count of 100, batch size of 16, learning rate of 0.1 and Nadam optimizer provide the most optimal results with an accuracy value of 86%, precision of 86%, recall of 84% and f1-score 84% in the training data used. This shows that the model is able to properly classify data according to its class. This study only focuses on the classification of chilli leaf disease, it is hoped that in the next study, it can classify the diseases that attack chilli leaves. Need to do a comparison with other CNN architectures like DenseNet, Resnet and Alexnet to get better accuracy.

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