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Corn Leaf Disease Classification Optimization Using Resnet50 Architecture Utilizing Bayesian Optimization

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ABSTRACT

This research aims to optimize the classification of diseases on corn leaves using Convolutional Neural Network (CNN) architecture, ResNet50, combined with hyperparameter optimization techniques using Bayesian Optimization. The dataset used comes from Kaggle, consisting of four classes of corn leaf diseases, namely corn leaf spot, leaf rust, corn leaf blight, and healthy corn leaves. Data pre-processing was done to balance the amount of data between classes and reduce the risk of overfitting. This study tested various scenarios, including the use of the original dataset and a pre-processed dataset. The experimental results show that the use of Bayesian Optimization in hyperparameter search gives better results than manual parameter setting. The scenario with hyperparameter optimization using Bayesian Optimization technique on the pre-processed dataset shows an increase in accuracy by 5% (87.79%) compared to the scenario without optimization (82.82%). This research concludes that hyperparameter optimization techniques and proper data pre-processing can improve the performance of CNN models in corn plant disease classification, providing the potential to assist farmers in detecting diseases earlier and reducing the economic losses incurred.

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1. INTRODUCTION

Maize is an important food crop in many countries. Maize plant diseases are one of the biggest obstacles in maintaining productivity and plant health. [1]. These diseases not only impact crop yields, but also cause significant economic losses for both farmers and the country. Given that maize is an important commodity in both domestic and export markets, disruptions caused by these plant diseases can affect the supply chain extensively, all the way to the international market.[2]. Some common diseases that attack maize plants are northern leaf blight (NLB), southern leaf blight (SLB), and gray leaf spot (GLS). [3].

This corn plant disease must be dealt with quickly and precisely. Traditional methods with manual observation require considerable time and expertise, and are prone to errors. So there is a need for technology to increase efficiency in controlling corn plant diseases. [4]. With the emergence of these challenges, recent research has begun to utilize intelligent technologies such as machine learning to more effectively identify and classify maize leaf diseases. [5]. The first research conducted by [6] It focuses on developing a corn leaf disease classification model using Convolutional Neural Network (CNN) based on EfficientNet-B0 and ResNet-50. The test results showed that the EfficientNet-B0 model achieved an accuracy of 94%, while the ResNet-50 model achieved an accuracy of 93%. The EfficientNet-B0 model is slightly superior in terms of accuracy compared to ResNet-50. This paper offers suggestions for future researchers to explore other CNN models, as well as optimize the data preprocessing stage to reduce overfitting problems, and conduct further experiments with different parameters to get maximum results. Further research conducted by [7] compared 10

Convolutional Neural Network (CNN) models including DarkNet-53, DenseNet-201, GoogLeNet, Inceptionv3, MobileNetv2, ResNet-18, ResNet-101, ShuffleNet, SqueezeNet, and Xception to classify four types of corn diseases. Several processes were performed, including data pre-processing, data augmentation, and parameter setting. The results showed that the Inceptionv3 and ResNet101 architectures achieved the highest accuracy compared to the other architectures.. The third research was conducted by [8] The EfficientNet-B0 architecture was used and compared with several other architectures such as Inception V3, VGG16, ResNet50, ResNet101, ResNet152, and DenseNet121, to determine the optimal classification model. The experimental results show that the proposed model achieves 98.85% accuracy and outperforms the compared models..

Research that experimented with three CNN architectures, namely AlexNet, ResNet-50, and SqueezeNet was also conducted by [9] This research also applies hyperparameter optimization using Bayesian optimization to select optimal training parameters, as well as data augmentation to correct data imbalance. Experimental results show that ResNet-50 and SqueezeNet have the best results in terms of F1-score with an average score of 96%. The last research conducted by [10] Also conducted experiments with three CNN architectures, namely AlexNet, SqueezeNet, and Xception. Each architecture was tested using three different optimizations: ADAM, RMSProp, and SGDM, to see the best performance of each model in corn leaf disease classification. The experimental results showed that Xception performed the best with a testing accuracy of 97.3%, followed by SqueezeNet with 95.7%, AlexNet with 94.3%, and CNN with 92.6%. The ADAM optimizer proved to give the best results compared to other optimizers in terms of accuracy and other metrics.

Results from previous studies have shown that CNNs can provide high accuracy in corn leaf disease classification, but challenges remain in terms of overfitting, architecture optimization, and proper parameter selection [11]. For example, several studies have shown that architectures such as ResNet-50, Xception, and Inception capable of achieving high accuracy, but there has been no in-depth exploration of the influence of optimization parameter selection and data preprocessing techniques on improving model performance.

In this context, this research proposed to optimize the classification of corn leaf diseases using CNN (Convolutional Neural Network) architecture namely Resnet50 which has been proposed in previous research. The Corn Disease dataset available on Kaggle is used as the main data to train and test these models, before training the researcher pre-processes the data to avoid overfiting. This research aims to optimize the model in classifying corn leaf diseases by using Bayesian optimization techniques to find parameters such as learning rate, dropout rate, and the number of filters used in the model. With proper optimization, it is expected that this system can provide a reliable solution for farmers to identify diseases in corn plants early on. In addition to potentially increasing agricultural productivity, this research is also expected to reduce economic losses due to diseases that attack corn plants.

2. METHOD

This section describes the research methods used to build and evaluate the performance of the model. Necessary information such as the method chosen to obtain the data set, data preparation techniques, data analysis techniques, etc. as shown in figure 1.

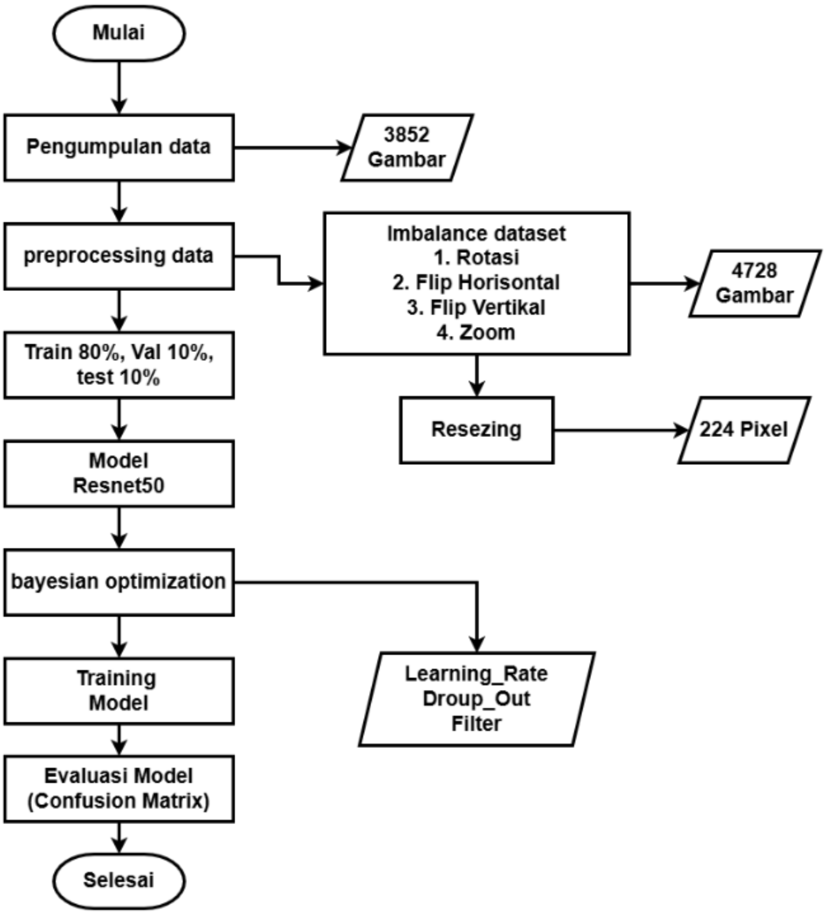

Figure 1: Research Stages

2.1. Dataset

This research uses a dataset derived from kaggle data which consists of 4 classes consisting of 3,852 images [12] Three classes are corn plant diseases, corn leaf spot, leaf rust, corn leaf blight, and 1 class is healthy corn leaves. This dataset consists of 513 images of corn leaf spot, 1192 images of leaf rust, 985 images of corn leaf blight, and 1162 images of healthy corn leaves. Figure 2 shows the samples taken from the dataset.

Maize Leaf Spot

Healthy Corn Leaf

Leaf Rust

Corn Leaf Blight

Figure 2. Dataset

2.2. Preprocessing Data

This stage is carried out with the aim that the data used in the model becomes cleaner, structured, and ready to be processed, with the aim of maximizing the results of corn leaf disease classification [13],[14]. This process involves Imbalance dataset rescaling, Resizing, Batching.

2.1.1. Imbalance

At this stage, the dataset used for the classification of corn plant diseases is 4 classes with a total of 3852 images, table 1 displays the number per class. From the dataset used, before entering the next process the researcher pre-processes the data, namely balancing the dataset to 4728 images with augmentation techniques such as rotation, horizontal flip, vertical flip, and zoom which aims to improve the quality and quantity of images to increase data diversity so as not to experience overfiting during training [15]. The results of the dataset imbalance process are presented in table 2.

Table 1. Total 4 class dataset before imbalance

No	Penyakit Daun	Jumlah gambar
1	Common_Rust	1192
2	Healthy	1162
3	Blight	985
4	Gray_Leaf_Spot	513
	Total	**3.852**

Table 2. Total 4 class dataset after imbalance

No	Penyakit Daun	Jumlah gambar
1	Common_Rust karat	1192
2	Healthy	1162
3	Blight hawar	1185
4	Gray_Leaf_Spot bintik	1189
	Total	**4728**

2.1.2. Rescaling

This step serves to convert pixel values from a scale of 0-255 into a smaller range of values, such as 0-1 or -1 to 1, so as to speed up the learning process and reduce numerical errors.

2.2.3. Resizing

Resizing aims to have uniform dimensions, as CNNs usually require input of a consistent size. For example, all images are resized to 224x224 pixels.

2.2.4. Batching

The function of this process. This division helps the model train with less memory than processing the entire dataset at once.

2.3. Dataset Sharing

At this stage, the prepared data is divided into three parts: 80% training set, 10% testing, and 10% validation. This step ensures that the model can be trained effectively and its performance can be evaluated accurately [16].

2.4. Resnet50 model and hyperparameter search

After pre-processing and dividing the dataset, modeling was performed to find the hyperparameters of learning_rate, dropout, and number of filters. Bayesian Optimization was used with the range of learning_rate: (1e-4, 1e-2) which defines that the search range for the learning_rate hyperparameter is 0.0001 to 0.01., dropout: (0.1, 0.5), and filters: (16, 64), which aims to find the combination of hyperparameters that gives the best performance. Once the hyperparameters are found, training is performed with varying epochs for the Resnet50 architecture [17].

2.5. Model Evaluation (Confusion Matrix)

The model was evaluated using confusion matrices to gain a deeper understanding of the model's prediction error. [18]. Each element in the confusion matrix indicates how many predictions are correct or incorrect for each class, thus providing a clear insight into where the model often misclassifies images.

3. RESULTS AND DISCUSSION

In this test, researchers used Lenovo v130 14 ikb laptop software with core i3 gen specifications, 8 ram, 256 gb ssd and windows 11 pro operating system and used Visual Studio Code and Google Colab pro tools. In the experiments conducted, this research produced several significant findings related to the classification of corn plant diseases using the CNN model with the ResNet50 architecture.

3.1. Scenario performed

In the various scenarios conducted, as shown in Table 3, the first experiment was conducted using the original dataset obtained from kaggle public data. The second experiment was conducted using a pre-processed and imbalanced dataset. This research focuses on finding hyperparameters using the Resnet-50 architecture and comparing it with the Resnet-50 architecture without using hyperparameters.

Table 3. Scenarios

No	Arsitektur	Hyperparameter	Dataset
1	Resnet-50	Bayesian Optimization	Original
2	Resnet-50	Bayesian Optimization	Pre-processing
3	Resnet-50	Manual	Original
4	Resnet-50	Manual	Pre-processing

3.2. Hyperparameter Search

At this stage, hyperparameter search using Bayesian Optimization technique is used with the range of learning_rate: (1e-4, 1e-2) which defines that the search range for hyperparameter learning_rate is 0.0001 to 0.01., dropout: (0.1, 0.5), and filters: (16, 64), which aims to find the hyperparameter combination that gives the best performance. The results of the hyperparameter search with the Bayesian Optimization technique on the Resnet50 architecture are shown in Table 4, which results in a hyperparameter learning_rate of 0.0003, dropout of 0.2427, and filters of 63.88.

Table 4. Hyperparameter search results

iter	target	Batch_size	dropout	filters	kernel	Learning_rate
1	0.7589	0.2145	49.43	26.89	4.103	0.007223
2	0.716	36.31	0.4923	48.87	3.962	0.003982
3	0.6993	32.47	0.3916	37.05	3.119	0.004041
4	0.7566	54.68	0.3266	22.92	4.27	0.003705
5	0.6181	61.95	0.4711	36.94	3.01	0.005247
6	0.7088	47.01	0.1407	18.44	4.681	0.004503
7	0.7136	60.58	0.3384	17.36	3.727	0.007392
8	0.7852	44.86	0.1272	32.4	4.868	0.001825
9	0.7589	40.75	0.219	28.18	4.355	0.005302
10	0.7088	45.3	0.2797	39.42	3.183	0.007249
11	0.79	16.2	0.2427	63.88	3.12	0.0003
12	0.7375	22.57	0.426	63.74	4.329	0.005099
13	0.7232	16.08	0.3522	57.39	4.42	0.009255

Best parameters found: {'batch_size': 16.19751205361355, 'dropout_rate': 0.24274056494098437, 'filters': 63.87593010459406, 'kernel_size': 3.120183684861207, 'learning_rate': 0.000300032862403894}

3.3. Results

The results of training from several scenarios that have been carried out using the Resnet50 architecture, the first scenario shown in Figure 3, using hyperparameter search with Bayesian optimazation techniques on the original dataset resulted in an accuracy of 83.72%, while the second scenario shown in Figure 4, using hyperparameter search with Bayesian optimazation techniques on a balanced dataset resulted in an accuracy of 87.79%, an increase of 5%. In the third scenario shown in Figure 5, researchers set the parameters manually on the original dataset resulting in an accuracy of 78.74%, while the fourth scenario shown in Figure 6 is the same. The researcher set the parameters manually on the original dataset resulting in an accuracy of 82.82%.

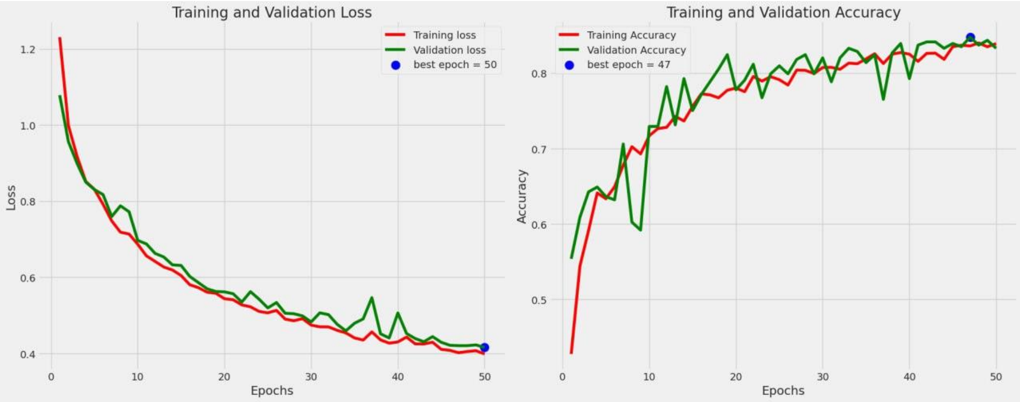

Figure 3. Graphical Results of the first Scenario

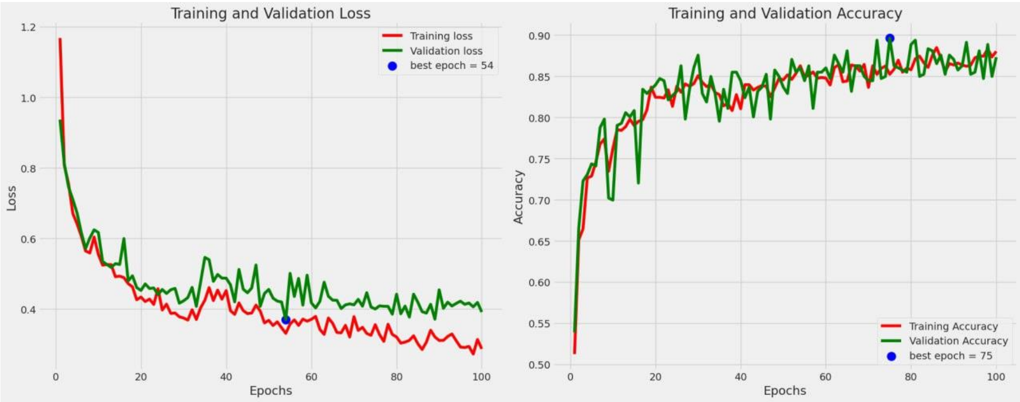

Figure 4. Graphical Results of the second Scenario

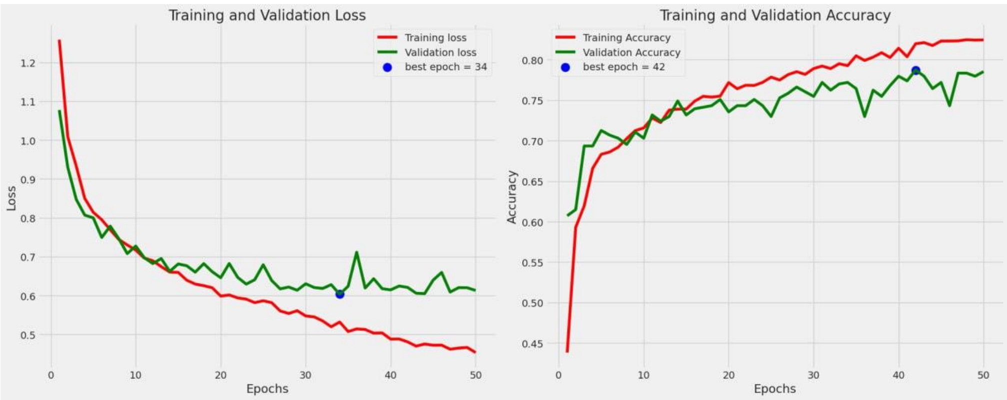

Figure 5. Graphical Results of the third Scenario

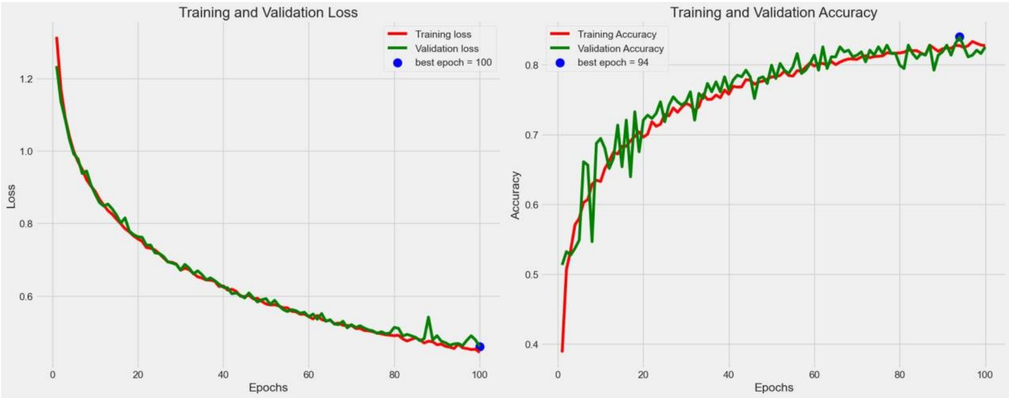

Figure 6. Graphical Results of the fourth Scenario

4. CONCLUSION

Based on the results described, this study shows that hyperparameter optimization using the Bayesian Optimization technique can significantly improve the performance of the model in the classification of diseases on corn leaves. The experiments conducted showed that the scenario with the use of Bayesian Optimization on the balanced dataset resulted in the highest accuracy of 87.79%, which is an improvement of 5% compared to the other scenarios. Pre-processing, such as dataset balancing, proves to be very important in reducing the risk of overfitting and improving the quality of classification results. By using a CNN architecture such as ResNet50, coupled with proper optimization, this research can make a great contribution to the development of an automated corn plant disease detection system. In addition, researchers suggest increasing the dataset or conducting a more thorough dataset selection, especially for disease classes that have visual similarities, such as corn leaf spot and corn leaf rust. This can improve the accuracy of the model in distinguishing between very similar disease types. Hopefully, the results of this study can assist farmers in detecting maize plant diseases more accurately and timely, which in turn will reduce economic losses caused by plant diseases and increase overall agricultural productivity.

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