Accredited Ranking SINTA 2
Decree of the Director General of Higher Education, Research and Technology, No. 158/E/KPT/2021
Validity period from Volume 5 Number 2 of 2021 to Volume 10 Number 1 of 2026

Published online on: **http://jurnal.iaii.or.id**

JURNAL RESTI
(Rekayasa Sistem dan Teknologi Informasi)
Vol. 7 No. 2 (2023) 326 - 333 ISSN Media Electronic: 2580-0760

Leaf Image Identification: CNN with EfficientNet-B0 and ResNet-50 Used to Classified Corn Disease

Wisnu Gilang Pamungkas[1], Muchammad Iqbal Putra Wardhana[2], Zamah Sari[3], Yufis Azhar[4]
[1,2,3,4]Informatika, Teknik, Universitas Muhammadiyah Malang
[1]wisnugilang26@gmail.com, [2]Iqbalwrdhn24@gmail.com, [3]zamahsari@umm.ac.id, [4]yufis@umm.ac.id

Abstract

Corn is the second largest commodity in Indonesia after rice. In Indonesia, East Java is the largest corn producer. The first symptom of the disease in corn plants is marked by small brownish oval spots which are usually caused by the fungus Helminthoporium maydis, if left unchecked, farmers can suffer losses due to crop failure. Therefore it is important to provide treatment for diseases in corn plants as early as possible so that diseases in corn plants do not spread to other plants. In this study, the dataset used was taken from the kaggle website entitled Corn or Maize Leaf Disease Dataset. This dataset has 4 classifications: Blight, Common Rust, Grey leaf spot, and Healthy. This study uses the Convolutional Neural Network method with 2 different models, namely the EfficientNet-B0 and ResNet-50 models. The architectures used are the dense layer, the dropout layer, and the GlobalAveragePooling layer with a dataset sharing ratio of 70% which is training data and 30% is validation data. After testing the two proposed scenarios, the accuracy results obtained in the test model scenario 1, namely EfficientNet- B0 is 94% and for the second test model scenario, namely ResNet-50, the accuracy is 93%.

Keywords: *diseases of corn plants; efficientnet-B0; resnet-50; convolutional neural network*

1. introduction

Corn (Zea Mays L.) is the third most important source of food needs after wheat and rice. These three food sources can meet more than half of human calorie needs (Perera & Weerasinghe in [1]). In fact, according to FAO (2016), the requirement for corn will continue to increase to reach 3.3 billion tons in 2050 [1]. Corn is a crop that has the potential to be developed, this is because corn has become a supporter of national food security.

Corn is not only used as food, in other benefits corn can be used as feed, pharmaceutical industry materials, and snacks. As the demand for feed in Indonesia soars, it is estimated that the need for corn will continue to increase [2]. In the growth of corn in Indonesia, East Java Province plays a significant role by providing 40% of the total national production. However, diseases that attack corn plants can cause many losses to farmers [3].

Various things must considered for cultivating corn plants, namely paying attention to the seeds to be planted, the right time for planting, proper land management, the planting process, and well handling if the plants are diseased. These factors must be considered so that corn productivity is in good condition and continues to increase [4].

Corn plants are very susceptible to disease. In general, diseases that attack corn plants are initially marked by changes in the leaves. Disease that starts on the leaves is usually caused by the fungus Helminthosporium Turcium, the first symptom is small oval spots that spread gradually [5].

There is also a disease on the corn leaves caused by the fungus Helminthoporium Maydis, Characteristics of the disease on corn leaves are characterized by the presence of brownish-yellow spots that are elongated or oval [6].

Classification of diseases in corn plants can generally be done through the sense of human sight. Corn plants infected with the disease will be marked by the appearance of changes visually. Detecting corn leaf disease manually has the main challenge, namely the number of leaves that must be identified and there are differences in understanding among humans [7].

the lack of knowledge of farmers about corn plant diseases results in the wrong identification of corn plants that are attacked by diseases so errors often occur in handling diseases that attack corn plants [8]. Slow handling of diseases in corn plants diseases can affect

Accepted: 01-12-2022 | Received in revised: 20-02-2023 | Published: 26-03-2023

the transmission of other corn plants [9]. Slow handling of diseases in corn plants can also cause increased costs for caring for corn plants that have been affected by the disease [10]. To understand the symptoms of disease in corn plants, an expert in agriculture is needed, but not all regions have experts in agriculture, especially experts in corn plants [11].

With the problems faced by farmers in identifying diseases found in corn plants, a system is needed to make it easier to determine the disease through identification so that farmers get the right solution in handling corn plant diseases [2]. Farmers can use a computer system that can be used as a substitute for the role of an expert if there are obstacles in handling corn plant diseases [12].

Research conducted to classify plant diseases through leaf images can have a positive impact on farmers. In classified leaf images using deep learning and transfer learning algorithms. The deep learning algorithm that is often used is the Convolutional Neural Network. The Convolutional Neural Network (CNN) algorithm is a development of the Multilayer Perceptron (MLP) which has been designed to process two-dimensional data [13].

The CNN method is very commonly used for image classification because this method can produce the most significant accuracy in image recognition [14]. Reliability The performance of the CNN method is exemplary in several fields related to Computer Vision and image processing [15].

Responding to the problems above, researchers conducted research that refers to research that has been done. Previous research related to the classification of corn leaf images has been carried out by Faisal Dharma Adhinata, Gita Fadila Fitriana, Aditya Wijayanto, Muhammad Pajar Kharisma Putra (2021) with the title "Corn Disease Classification Using Transfer Learning and Convolutional Neural Network" proposing the application of the Convolutional Neural Network method with the model DenseNet-201 with a total dataset of 4188 images and divided into 4 classification classes with details namely blight 1146 data, common rust 1306 data, gray leaf spot 574 data and healthy 1162, getting the best accuracy result of 93% [16].

Previous research related to the classification of corn leaf images has been carried out by Eko Hari Rachmawanto and Heru Pramono Hadi (2021) with the title "Optimization of Feature Extraction in KNN in Classification of Corn Leaf Disease" proposing the application of the algorithm used is KNN-HSV-GLCM with a dataset totaling 160 training data and 40 test data, with a k value of 3 then the pixel spacing is 1 getting 85% accuracy results, and at a k value of 3 then the pixel spacing is 3 getting 70% accuracy value which is the lowest result [3].

Previous research regarding the classification of corn leaf imagery has been carried out by Ivan Pratama Putra, Rusbandi, Derry Alamsyah (2022) with the title Classification of Corn Leaf Disease Using a Convolutional Neural Network" proposing the application of the CNN algorithm and the model used, namely Resnet50 with a dataset division ratio of 80:20, using 3 optimizers Adam, Nadam, and SGD and the number of epochs carried out 20 times to get the best accuracy of 98.4% with the Adam optimizer [17].

Previous research related to "Classification of Diseases in Robusta Coffee Plants Based on Leaf Image Using a Convolutional Neural Network" was conducted by Savira Aginta Sabrina and her colleagues (2022), using the convolutional neural network method with the proposed model being efficientnet-B0 using two optimizers namely adam and Rmsprop, the accuracy results obtained by using these 2 optimizers are 91% [18].

Previous research related to the classification of corn leaf images has been carried out by Mit Atila A, Murat Ucar, Kemal Akyo, and Emine Ucar (2021) with the title "plant leaf classification using the deep learning Efficientnet model" proposing the application of efficientNet with a comparison of other CNN models, namely AlexNet, ResNet50 , VGG16, and Inception V, with a total dataset of 54,305 image data and containing 38 classes from 14 different species, obtained the best accuracy results on the efficienNet-B5 model of 99.91% and EfficientNet-B4 of 99.97% [19].

Previous research related to the classification of corn leaf images has been carried out by Abdul Jalil Rozaqi, Andi Sunyoto, and Rudyanto Arief (2021) with the title "Detection of Diseases in Potato Leaves Using Image Processing with the Convolutional Neural Network Method" proposing the application of the algorithm used is the Convolutional Neural Network, with the number of datasets is 1152 and divided into 4 classification classes, using a dataset size of 150x150 with a sharing ratio of 80% training data and 20% validation data to get 94% accuracy value [20].

Previous research related to the classification of corn leaf imagery has been carried out by Mohtar Khoiruddin, Apri Junaidi, and Wahyu Andi Saputra (2022) with the title "Classification of Rice Leaf Disease Using a Convolutional Neural Network" times and got an accuracy value of 98% [21].

Previous research related to the classification of corn leaf images has been carried out by Alang Mulya Lesmana, Ronna Putri Fadhillah, Chaerur Rozikin (2022) with the title "Disease Identification in Potato Leaf Image Using a Convolutional Neural Network (CNN)" proposing the application of the algorithm used is CNN with datasets from 5400 image data that has been divided into 3 classes, namely healthy images,

DOI: https://doi.org/10.29207/resti.v7i2.4736

early Hawar images, and late Hawar images get 99% of the highest accuracy results on validation data [10].

Based on the research above, the purpose of this study was to improve the results of the accuracy of previous studies conducted by[16]and compare with the proposed model, the proposed model is EfficientNet-B0 and ResNet-50 with the dataset used taken from the Kaggle website entitled Corn or Maize Leaf Disease Dataset. This dataset has 4 classifications with a total of 4188 image data with details for each class, namely blight 1146 image data, common rust 1306 image data, gray leaf spot 574 image data, and healthy 1162 image data.

2. Research Methods

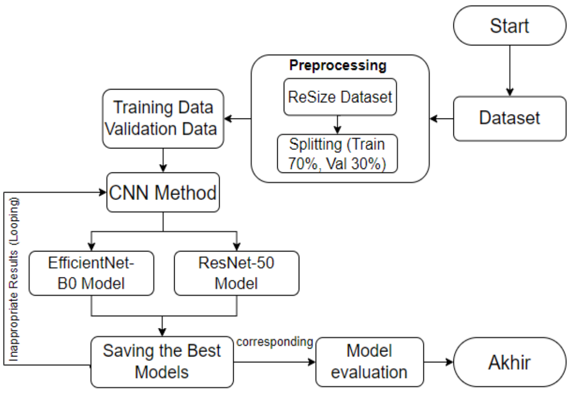


Figure 1. Flowchart of the research method

The research method section, it is explained the stages of the research flow that will be carried out, which can be seen in figure 1. This research flow starts by taking the dataset on Kaggle, then carrying out the preprocessing process by changing the size of the dataset and dividing process data by dividing train data and validation data, in the next stage, the image will be model trained using the EfficientNet-B0 and ResNet-50 models to get maximum results, and in the final stage, a model evaluation will be carried out.

2.1 Dataset

The use of dataset in this study comes from the web Kaggle with the title Corn or Maize Leaf Disease Dataset. This dataset has 4 classifications with a total of 4188 data with details for each class, namely blight 1146 data, Common rust 1306 data, gray leaf spot 574 data, and healthy 1162 data [22], as seen in figure 2.

2.2 Preprocessing

After collecting data taken from the Kaggle web as described, in the next stage, data sharing is carried out. Before split data sharing, the image size is first changed to 224 x 224. After the image size becomes one size, then after that the image data the data sharing process is carried out, namely the distribution of training data and validation data. The ratio used for this research is 70% training data and 30% validation data.

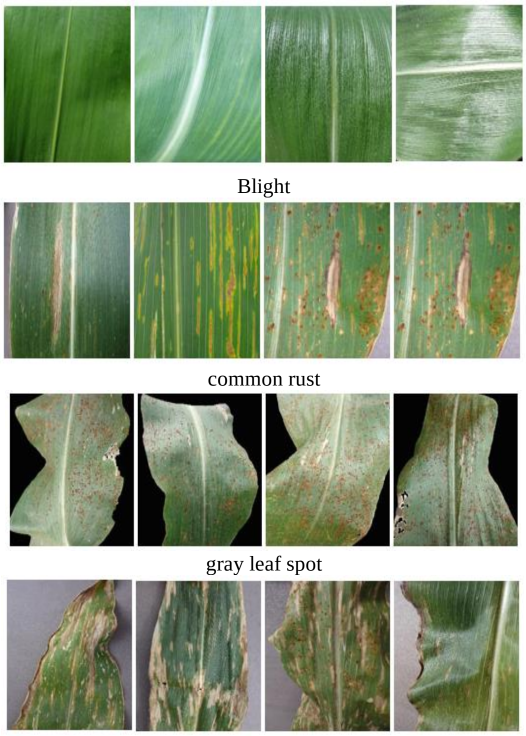


Figure 2. An example of a dataset image

2.3. Model Architecture

The method used in this research is the CNN method, the models used are the efficientNet B0 model and the RestNet50 model to identify corn plant diseases. The efficientNet-B0 model has a total of 230 layers [23]. Meanwhile, the ResNet-50 model has a total layer depth of 50 [24]. The model in this study uses a two-layer base model. Each uses Global Average Pooling 2D, Dense (512), uses Dropout (0.5) and (0.1), optimizer adamax and rmsprop, and uses Relu activation. Global Average Pooling is made so that data can be segmented and also the problem of overfitting can be overcome [25]. The use of the Global Average Pooling 2D layer also works so that the selected image has average features [26]. The architectural design of the model can be seen in table 1.

Table 1. CNN architectural model

Layer	Filter	Kernel Size	Activation
EfficientNet-B0 input (224, 224)	-	-	-
ResNet-50 input (224, 224)	-	-	-
GlobalAverage Polling2D	-	-	-
Dropout	0.5, 0.1	-	-
Dense	512	-	relu
Dropout	0.5, 0.1	-	-
Dense	224	-	relu
Dense	4	-	softmax

DOI: https://doi.org/10.29207/resti.v7i2.4736

3. Results and Discussions

This stage explains the results of the classification of corn plant diseases that have been obtained using predetermined models, namely EfficientNetB0 and RestNet50. The training process will be carried out with the EfficientNet-B0 and ResNet-50 architectures using Google collab with the device specifications using the programming language python 3.7.15, google collab software, and hardware used with 10th Gen Intel(R) Core (TM) i5-10210U CPU @ 2.11 GHz processor specifications, 12GB Ram memory, AMD Radeon 530 Series GPU.

In the first stage, taking the dataset on the Kaggle site entitled Corn or Maize Leaf Disease Dataset, this dataset has 4 classification classes, namely blight, common rust, gray leaf spot, and healthy, then in the next stage the data is resized to 224 x 224 so that the image size be the same size, after resizing the image then the data is divided into training data and validation data, and the ratio used is 70% training data and 30% validation data.

In the next stage, training data is carried out using the selected models, namely efficientNet-B0 and restNet-50 with different parameters. Table 2 explains the 2 scenarios that will be carried out with different models and different parameters.

Table 2. Scenario test model

Scenario	Description	Filter
Model 1	*EfficientNet-B0 model (input 224,224)*	*Dropout (0.5) Dense (512)*
Model 2	*ResNet-50* model (224, 224)	*Dropout (0.1) Dense (512)*

3.1 The first model scenario

In testing scenario 1, the proposed model is efficientNet B0, the parameters used in scenario 1 testing model are listed in table 3.

Table 3. Scenario architecture test model 1

Layer	Filter	Kernel Size	Activation
EfficientNet-B0 input (224, 224)	-	-	-
GlobalAverage Polling2D	-	-	-
Dropout	0.5	-	-
Dense	512	-	relu
Dropout	0.5	-	-
Dense	224	-	relu
Dense	4	-	softmax

The architecture used in model 1 is shown in table 3 with details Dropout = 0.5, Dense = 512 with relu activation, Dropout = 0.5, Dense = 224 with relu activation, Dense = 4 with softmax activation and using the Adamax optimizer, and doing epoch 100 times.

After carrying out the test, a graph plot of the results that have been obtained will be made. This graph functions to see whether the results obtained have increased or not for each train, and also whether there is overfitting or underfitting in the model used, namely EfficientNet-B0, in Figure 3, and is the result of the plot that has been tested.

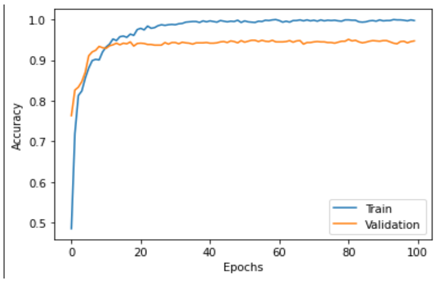


Figure 3. Results of model scenario accuracy plot 1

In figure 3 it can be seen from epoch 0 to epoch 20 that the chart is moving unstable, from epoch 21 to epoch 100 the graph shows movement that has begun to stabilize. The movement of the graph is unstable because the model is still in the learning stage, while the graph has begun to show a stable movement because the model has learned from the dataset.

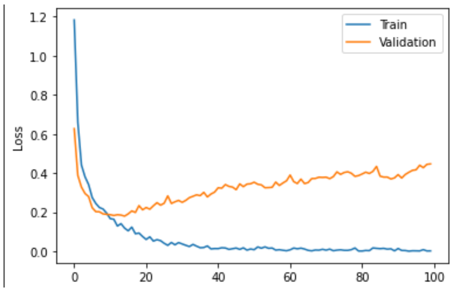


Figure 4. Results of model scenario loss plot 1

Figure 4 shows that the graphic movement in the confusion matrix scenario 2 is unstable, starting from epoch 0 to epoch 6, machine learning is still in the dataset learning stage, then in epoch 7 to 100 there is an unstable graphic movement and causes overfitting, thing This is due to poor machine learning.

After the results of the training graph are obtained, the next step is to evaluate system performance in the first scenario, model evaluation can be seen using the classification report and also by looking at the confusion matrix image that was obtained in the first test scenario. The report on the results of the scenario 1 test classification is shown in table 4.

Table 4. Report on the results of model classification 1

Classification Report	
Accuracy	94%
Precision	93%
Recall	91%
F1-Score	92%

Table 4 shows the results of the classification report in test scenario 1 which was carried out and obtained

DOI: https://doi.org/10.29207/resti.v7i2.4736

results of 94% accuracy, precision = 93%, recall = 91%, and f1-score = 92%.

After seeing the classification report in table 4, the next model evaluation is by looking at the confusion matrix image. At the same time, it measures whether the machine learning model used can predict the amount of data correctly or incorrectly [19]. The results of the confusion matrix in the model 1 test scenarios are shown in Figure 5

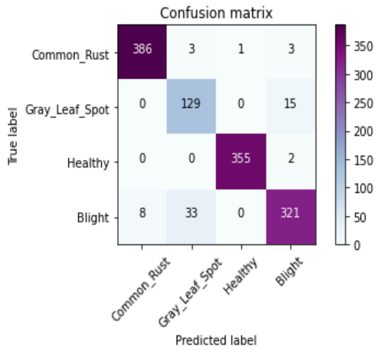


Figure 5. The results of the confusion matrix model 1

Figure 5 shows the results of the confusion matrix in the first test scenario. From the results obtained in the confusion matrix above, there are 4 classification classes, namely common rust, gray leaf spot, healthy, and blight, it can be concluded that in the common rust class, there are 386 data that are predicted to be correct and 8 data that are predicted to be wrong, then in the gray leaf spot, there are 129 data that are predicted to be correct and 36 data that are predicted to be wrong, then in the healthy class there are 355 data that are predicted to be correct and 1 data that is predicted to be wrong, while in the blight class, there are 321 data that are predicted to be correct and 20 data are predicted to be wrong.

After seeing the results of the model evaluation in scenario 1, the prediction results obtained can be seen in Figure 6.

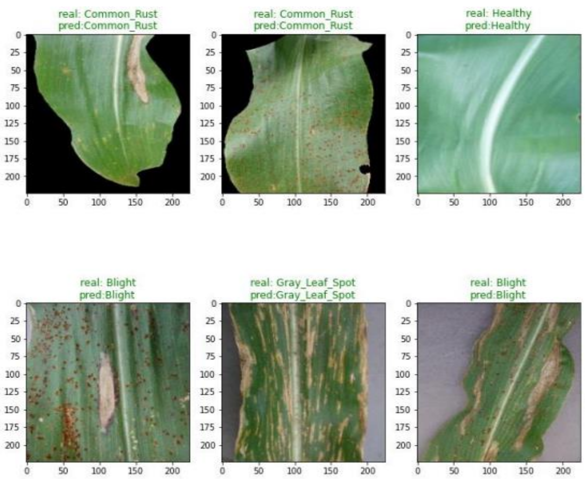


Figure 6. Prediction results of model scenario 1

In Figure 6 it can be concluded that the prediction results obtained are the machine learning model used which can predict accurately, the predictions and also the images that are trained get the same results.

3.2 The second model scenario

In testing scenario model 2 that is proposed is the ResNet-50 model, details of the parameters used in the second test scenario can be seen in table 5.

Table 5. Scenario architecture test model 2

Layer	Filter	Kernel Size	Activation
ResNet-50 input (224, 224)	-	-	-
GlobalAverage Polling2D	-	-	-
Dropout	0.1	-	-
Dense	512	-	relu
Dropout	0.1	-	-
Dense	224	-	relu
Dense	4	-	softmax

In table 5 the architecture used in testing the scenario 2 models with details using Dropout = 0.3, Dense = 1024 with relu activation, Dropout = 0.3, Dense = 224 with relu activation, and Dense = 4 with softmax activation.

After testing using the architecture above, a graphic plot will be made of the results that have been obtained, this graph functions to see whether the results obtained have an increase or not in each train, and also whether there is overfitting or underfitting in the model used, namely *ResNet- 50*, Graphic plot images can be seen in Figures 7 and 8.

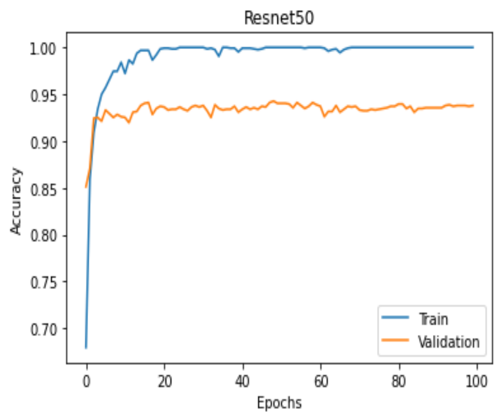


Figure 7. Results of model scenario accuracy plot 2

In Figure 7, it can be seen that from epoch 0 to epoch 19 the chart is moving unstable, from epoch 20 to epoch 35 the chart shows a stable movement, even though there is still unstable graphic movement but the chart is not too overfitting. The movement of the graph is unstable because the model is still in the dataset learning stage, while the graph has begun to show a stable movement because the model has already learned the dataset.

DOI: https://doi.org/10.29207/resti.v7i2.4736

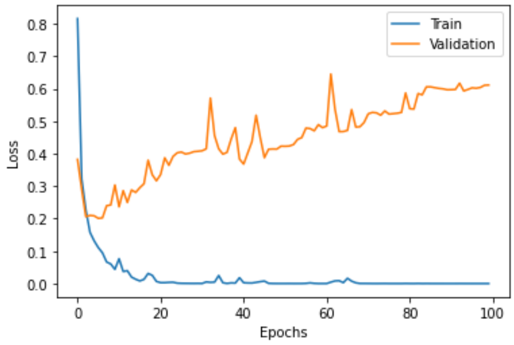


Figure 8. Results of model scenario loss plot 2

Figure 8 shows that the graphic movement in the confusion matrix scenario 2 is unstable, starting from epoch 0 to epoch 4, machine learning is still in the dataset learning stage, then in epoch 5 to 100 there is an unstable graphic movement and causes overfitting, thing This is due to poor machine learning.

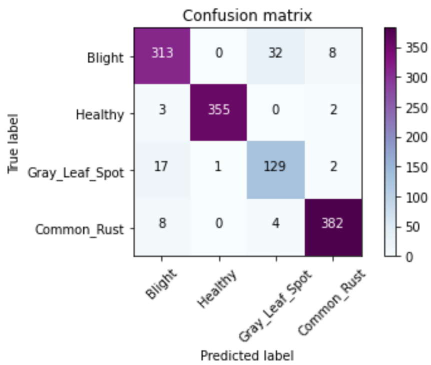
After the results of the training graph are obtained, the next step is to evaluate the performance of the model in the second scenario, model evaluation can be seen using the classification report and also by looking at the confusion matrix image that was obtained in the second test scenario. The report on the results of the classification in test scenario 2 can be seen in table 6.

Table 6. Report on the results of model classification 2

Classification Report	
Accuracy	94%
Precision	93%
Recall	91%
F1-Score	92%

Table 6 above shows the results of the classification report in test scenario 2, namely obtaining results of 93% accuracy, precision = 93%, recall = 92%, and f1-score = 92%.

After seeing the classification report above, the next model evaluation is by looking at the confusion matrix image as well as measuring whether the machine learning model used can predict the amount of data correctly or incorrectly [19]. The confusion matrix image can be seen in Figure 9.



\

Figure 9. The results of the confusion matrix model 2

Figure 9 shows the results of the confusion matrix in the second test scenario. It can be concluded that in the common rust class, there are 382 correct predictions, then 12 incorrect data predictions, and in the gray leaf spot class there are 129 correct predictions and 36 incorrect data predictions. data, then in the healthy class there were 355 correct predictions of data, then as much as 1 data was predicted incorrectly, and while in the blight class, there were 313 data that were correctly predicted then as many as 28 data were wrong data.

After evaluating the model using the confusion matrix and also the classification report, the next step is to look at the predictions of model 2 testing scenarios, which can be seen in Figure 10.

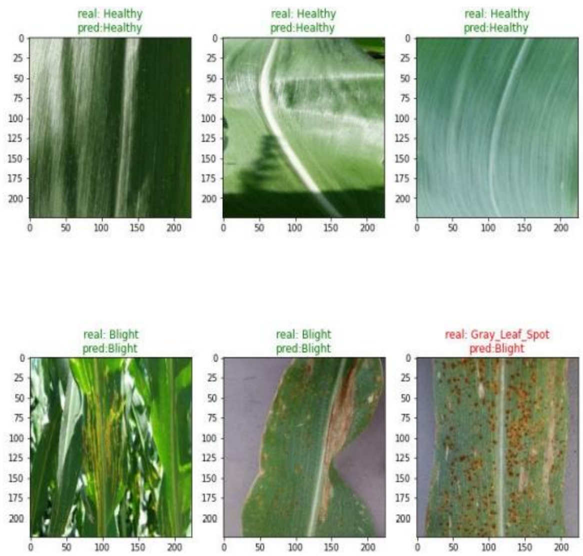


Figure 10. Prediction results of model scenario 2

In figure 10 it can be concluded that the prediction results obtained are the machine learning model used can predict well, and also the images that are trained get good results, even though there is one wrong prediction, the image given is gray leaf spots but the model predicts is blight.

After carrying out 2 test scenarios, the test architecture affects the test to get the best accuracy value. The results of testing the 2 scenarios that have been carried out are summarized in table 7.

Table 7. The results of the proposed model testing

Scenario	Accuracy	Precision	Recall	F1-Score
Model 1 (EfficientNet-B0)	94%	93%	91%	92%
Model 2 (*RestNet-50*)	93%	93%	92%	92%

Model evaluation was also carried out in this study with previous research [16]. Comparisons to the details of previous studies are summarized in table 8.

Table 8. Comparison table with previous research

Scenario	Dataset	Model	Accuracy
Adhinata et al [16]	*Corn or Maize Leaf Disease*	*DenseNet -201*	93%
Model 1	*Corn or Maize Leaf Disease*	*Efficient Net-B0*	94%
Model 2	*Corn or Maize Leaf Disease*	*ResNet-50*	93%

Based on the results of research using model test scenarios that have been carried out overall scenario model test 1 is better than previous research [16] by obtaining an accuracy of 94%.

4. Conclusion

Based on the research results, the first test model scenario, namely the EfficientNet-B0 model, obtained an accuracy of 94% higher than the model 2 test scenario, namely ResNet-50, which was 93%. The results obtained are influenced by several things including the balance of the number of datasets used, the division of the splitting ratio, the number of layers, and the number of inputs used. Suggestions for further research are to use the same research topic and dataset to modify it again at the preprocessing stage and try other CNN models such as VGG-19 to get maximum results.

References

[1] S. I. Ramadhani, Y. Masruni, and N. Aidawati, "Reaksi Ketahanan Beberapa Genotipe Calon Varietas Jagung Hibrida terhadap Tiga Penyakit Utama Jagung," *Seminar Nasional dalam Rangka Dies Natalis ke-45 UNS Tahun 2021*, vol. 5, no. 1, pp. 245–252, 2021.

[2] H. Mirsam, S. Suriani, A. T. Makkulawu, N. Djaenuddin, and F. Abdullah, "Evaluasi Ketahanan Genotipe Jagung Hibrida terhadap Penyakit Hawar Daun Maydis dan Karat Daun," *Prosiding Seminar Nasional Lahan Suboptimal ke-9 Tahun 2021*, pp. 305–313, 2021.

[3] E. H. Rachmawanto and H. P. Hadi, "Optimasi Ekstraksi Fitur Pada Knn Dalam Klasifikasi Penyakit Daun Jagung," *Dinamik*, vol. 26, no. 2, pp. 58–67, 2021, doi: 10.35315/dinamik.v26i2.8673.

[4] M. M. Suhadi, M. Alauddin Helmi, and W. Setiawan, "Simulasi Klasifikasi Hama Dan Penyakit Pada Jagung Dengan Naive Bayes," vol. 10, no. 1, 2021.

[5] M. R. Pahlevi, "Aplikasi Sistem Pakar Bebasis Web Untuk Diagnosa Penyakit Jagung," *Prosiding Seminar Nasional Teknologi …*, pp. 265–273, 2021, [Online]. Available: http://prosiding.unipma.ac.id/index.php/SENATIK/article/view/1921

[6] M. I. Rosadi, M. Lutfi, and S. Artikel, "Identifikasi Jenis Penyakit Daun Jagung Menggunakan Deep Learning Pre-Trained Model INFO ARTIKEL ABSTRAK", doi: 10.35891/explorit.

[7] J. Teknologi Informasi, R. Suhendra, and I. Juliwardi, "Identifikasi dan Klasifikasi Penyakit Daun Jagung Menggunakan Support Vector Machine," vol. 1, no. 1, pp. 29–35, 2022, [Online]. Available: http://jurnal.utu.ac.id/JTI

[8] U. Muhammadiyah Jember, R. Paleva, D. Arifianto, and A. Maryam Zakiyah, "Diagnosis Penyakit Tanaman Jagung Dengan Metode Dempster Shafer Diagnosis of Corn Plant Diseases Using the Dempster Shafer Method," 2022. [Online]. Available: http://jurnal.unmuhjember.ac.id/index.php/JST

[9] D. Irfansyah *et al.*, "Arsitektur Convolutional Neural Network (CNN) Alexnet Untuk Klasifikasi Hama Pada Citra Daun Tanaman Kopi," vol. 6, no. 2, 2021, [Online]. Available: https://data.mendeley.com/datasets/c5yvn32dzg/2.

[10] A. M. Lesmana, R. P. Fadhillah, and C. Rozikin, "Identifikasi Penyakit pada Citra Daun Kentang Menggunakan Convolutional Neural Network (CNN)," *Jurnal Sains dan Informatika*, vol. 8, no. 1, pp. 21–30, 2022, doi: 10.34128/jsi.v8i1.377.

[11] B. S. Palopo, "batang dan buah . Daun tanaman yang," vol. 12, pp. 42–50, 2022.

[12] Moh. A. Hasan, Y. Riyanto, and D. Riana, "Grape leaf image disease classification using CNN-VGG16 model," *Jurnal Teknologi dan Sistem Komputer*, vol. 9, no. 4, pp. 218–223, Oct. 2021, doi: 10.14710/jtsiskom.2021.14013.

[13] D. Hidayat, "Klasifikasi Jenis Mangga Berdasarkan Bentuk Dan Tekstur Daun Menggunakan Metode Convolutio Nalneural Network(Cnn) Classification Of Types Of Mango Based On Leave Shape And Texture Using Convolutio Nalneural Network(Cnn) Method," *Journal of Information Technology and Computer Science (INTECOMS)*, vol. 5, no. 1, 2022.

[14] R. Prabowo, A. Roudhoh, and F. Matematika dan Ilmu Pengetahuan Alam, "Klasifikasi Image Tumbuhan Obat Sirih dan Binahong Menggunakan Metode Convolutional Neural Network (CNN)."

[15] E. Oktafanda, "Klasifikasi Citra Kualitas Bibit dalam Meningkatkan Produksi Kelapa Sawit Menggunakan Metode Convolutional Neural Network (CNN)," *Jurnal Informatika Ekonomi Bisnis*, vol. 4, no. 3, pp. 72–77, 2022, doi: 10.37034/infeb.v4i3.143.

[16] F. D. Adhinata, G. F. Fitriana, A. Wijayanto, and M. P. K. Putra, "Corn Disease Classification Using Transfer Learning and Convolutional Neural Network," *JUITA: Jurnal Informatika*, vol. 9, no. 2, p. 211, 2021, doi: 10.30595/juita.v9i2.11686.

[17] I. P. Putra, R. Rusbandi, and D. Alamsyah, "Klasifikasi Penyakit Daun Jagung Menggunakan Metode Convolutional Neural Network," *Jurnal Algoritme*, vol. 2, no. 2, pp. 102–112, 2022, doi: 10.35957/algoritme.v2i2.2360.

[18] S. A. Sabrina and W. F. al Maki, "Klasifikasi Penyakit Pada Tanaman Kopi Robusta Berdasarkan Citra Daun Menggunakan Convolutional Neural Network," *eProceedings …*, vol. 9, no. 3, pp. 1919–1927, 2022, [Online]. Available: https://openlibrarypublications.telkomuniversity.ac.id/index.php/engineering/article/view/17997%0Ahttps://openlibrarypublications.telkomuniversity.ac.id/index.php/engineering/article/download/17997/17626

[19] Ü. Atila, M. Uçar, K. Akyol, and E. Uçar, "Plant leaf disease classification using EfficientNet deep learning model," *Ecol Inform*, vol. 61, no. June 2020, p. 101182, 2021, doi: 10.1016/j.ecoinf.2020.101182.

[20] A. J. Rozaqi, A. Sunyoto, and M. rudyanto Arief, "Deteksi Penyakit Pada Daun Kentang Menggunakan Pengolahan Citra dengan Metode Convolutional Neural Network," *Creative Information Technology Journal*, vol. 8, no. 1, p. 22, 2021, doi: 10.24076/citec.2021v8i1.263.

[21] M. Khoiruddin, A. Junaidi, and W. A. Saputra, "Klasifikasi Penyakit Daun Padi Menggunakan Convolutional Neural Network," *Journal of Dinda : Data Science, Information Technology, and Data Analytics*, vol. 2, no. 1, pp. 37–45, 2022, doi: 10.20895/dinda.v2i1.341.

[22] Smaranjit Ghose, "Corn or Maize Leaf Disease Dataset," *https://www.kaggle.com/datasets/smaranjitghose/corn-or-maize-leaf-disease-dataset*, 2020.

[23] D. R. Nayak, N. Padhy, P. K. Mallick, M. Zymbler, and S. Kumar, "Brain Tumor Classification Using Dense Efficient-Net," *Axioms*, vol. 11, no. 1, 2022, doi: 10.3390/axioms11010034.

[24] Jalu Nusantoro, Faldo Fajri Afrinanto, Wana Salam Labibah, Zamah Sari, and Yufis Azhar, "Detection of Covid-19 on X-Ray Image of Human Chest Using CNN and Transfer Learning," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 6, no. 3, pp. 430–441, Jun. 2022, doi: 10.29207/resti.v6i3.4118.

[25] M. M. Nayak and S. D. K. Anjanappa, "Brain Tumor Classification for MR Images using Convolution Neural Network with Global Average Pooling," *International Journal of Intelligent Engineering and Systems*, vol. 14, no. 6, pp. 40–49, Dec. 2021, doi: 10.22266/ijies2021.1231.05.

[26] M. A. Purnama Wibowo, Muhammad Bima Al Fayyadl, Yufis Azhar, and Zamah Sari, "Classification of Brain Tumors on MRI Images Using Convolutional Neural Network Model EfficientNet," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 6, no. 4, pp. 538–547, Aug. 2022, doi: 10.29207/resti.v6i4.4119.

DOI: https://doi.org/10.29207/resti.v7i2.4736