Journal of Information System and Application Development
Volume 2 Number 2 September 2024 page 111-121
P-ISSN: 2988-5698 ǀ E-ISSN: 2988-4721
https://jurnal.unmer.ac.id/index.php/jisad

Image classification of leaf disease in corn plants (Zea Mays L.) using the MobileNetV2 method

Dellyan Achmad*, Oddy Virgantara Putra, Dihin Muriyatmoko
Program Study Informatics Engineering, Universitas Darussalam Gontor, Ponorogo, Indonesia

E-mail: *dellyanachmad@mhs.unida.gontor.ac.id

Abstract. One of the main problems leading to low yields and possible crop failure in maize, a crop of great importance to human civilization, is that plant diseases are discovered and treated too late, leading to more severe diseases and even crop failure. Using photos taken from the Kaggle platform and some field shots, this research seeks to develop a classification system that can identify different types of diseases present on maize leaves. The disease types identified include Common Rust, Gray Leaf Spot, and Bacterial Leaf Blight. MobileNetV2 uses a Convolutional Neural Network (CNN) design to handle resource-intensive processes. To produce a lightweight model, this CNN uses separate corner shifts. The dataset for this study was taken from field shooting and the Kaggle platform. The study found that the MobileNetV2 model clarified objects very well with 93.01% accuracy. This discovery will help farmers find diseases on corn leaves (Zea Mays L).

Keywords: classification, machine learning, Depthwise Separable Convolution, MobileNetV2

Submitted: 20-07-2024 ǀ **Accepted:** 09-08-2024 ǀ **Published:** 13-09-2024

How to Cite:
D. Achmad, O. V. Putra, and D. Muriyatmoko, "Image classification of leaf disease in corn plants (Zea Mays L.) using the MobileNetV2 method," *Journal of Information System and Application Development*, vol. 2, no. 2, pp. 111-121, September 2024, doi: 10.26905/jisad.v2i2.14004.

INTRODUCTION

One crop grown to meet food needs, corn, has long been a mainstay for most people living in the tropics, especially in Asia and Africa. Because of the various advantages offered by corn plants, corn is one of the important cultivated crops for human civilization [1].

Because the corn plant produces a large number of staple foods that are consumed by most of the people of Indonesia after rice, this plant has become one of the agricultural commodities that is actively sought after and promoted in almost all regions in Indonesia. The success of the corn crop harvest is a very influential component, and the cultivation of corn plants is one of the crucial things to pay attention to along with the increase in population and the increasing need for basic foods produced by this plant [2].

Based on Indonesia's increasing agricultural yields, it can be seen that the main factor that causes low crop yields and crop failures is the late detection and treatment of crop diseases before the disease reaches a severe stage, which causes crop failure. This happens even though the plant disease appears mild and small, but before the disease becomes serious and spreads, it is usually already showing symptoms. Most farmers have used chemicals in the form of pesticides as a practical way to speed up the healing process to overcome the severity of the disease. In addition to being harmful to the environment, the use of improper pesticides in quantities determined by the severity of the disease can be detrimental to farmers [3].

There are various types of diseases that attack corn plants, one of which is Common Rust or Leaf Rust, Gray Leaf Spot or Gray Leaf Spot, and Bacterial Leaf Blight. This disease is caused by fungi and bacteria, including:

DOI : 10.26905/jisad.v2i2.14004

1. Leaf rust disease, or common rust, is caused by three species of two general fungi and bacteria i.e. Puccinia sorghi Scw., P. polysora Underw., and Physopella zeae (Mains) Cunmins and Ramachar [4].
2. Gray Leaf Spot is a leaf fungal disease that attacks grasses. In grasses other than corn, the disease is caused by Pyricularia grisea, which only infects perennial ryegrass, tall fescue, and St. John's grass [4].
3. Bacterial leaf blight is caused by the bacterium Xanthomonas campestris pv. Oryzae. which is a disease that often infects corn plants, especially in irrigated rice fields throughout Indonesia [5].

This experiment found a problem formulation whose content is that the researcher solves the problem of corn farmers in identifying corn plant diseases (Zea Mays L) in order to improve the quality and quantity of corn crop yields. The purpose is to classify diseases in corn plants (Zea Mays L.) by applying the transfer learning method using the MobileNetV2 architecture. This experiment also has some problem limitations so that the researcher limits this experiment according to the Limits that have been created. So researchers conduct experiments involving AI (Artificial Intelligence) in classifying a category problem.

Artificial Intelligence is one of the most prominent examples of technological advancements in the modern era, artificial intelligence has become a much-talked about issue in recent years. Artificial intelligence has become a scourge in many fields around the world, but it can also maximize productivity, reduce problems, and save human resources. By using Deep Learning, one of the sub-fields of artificial intelligence, the agricultural industry is one that can apply artificial intelligence. With the help of this technology, the researchers can use image classification on corn plants to determine diseases. The classification process is part of artificial intelligence in a system to classify diseases in corn plants based on image processing. Several studies classify the image of disease objects in certain plants. One example is the identification and classification of diseases in corn leaves using the Support Vector Machine [6] and the Convolutional Neural Network method [7] .

MobileNetV2 is a pre-trained image classification model that has been trained on a variety of datasets. This is an improvement over the MobileNetV1 model, which adds reverse residue and shortcuts in the connections between the bottleneck [8] layers. Architectures are better suited for processing images that require less computation in order to be classified correctly. Both features are designed to address processes that require excessive computing [9]. Depthwise Convolution is a convolution that counts the contribution of each channel separately, so each filter in the convolution has a size per channel of 1. The convolution filter is used in calculating each 1-channel feature. Then Pointwise convolution 1x1 [10] which is useful for determining the desired channel output. This model has a total of about 17 Residual Bottleneck blocks [11]. With the advent of Depthwise and Pointwise Convolution, the computational burden associated with architectural models can be reduced. This allows the model to be built with fewer parameters, resulting in a more efficient implementation [11]. MobileNetV2 is an effective model for classifying the severity of maize leaf disease. Researchers can use the Pre-Processing model to determine whether the diseases experienced by corn leaves are in accordance with the disease category.

METHOD

The purpose of this study was to use the MobileNetV2 architecture to achieve the best accuracy results for image classification of maize leaf disease severity (Zea Mays L.). This architectural paradigm works well for categorizing images. To create a classification model in the image classification research, the researcher made the following research stages as shown in Figure 1.

A. Data Collection
B. Pre-Processing
C. Processing
D. Trial and Validation

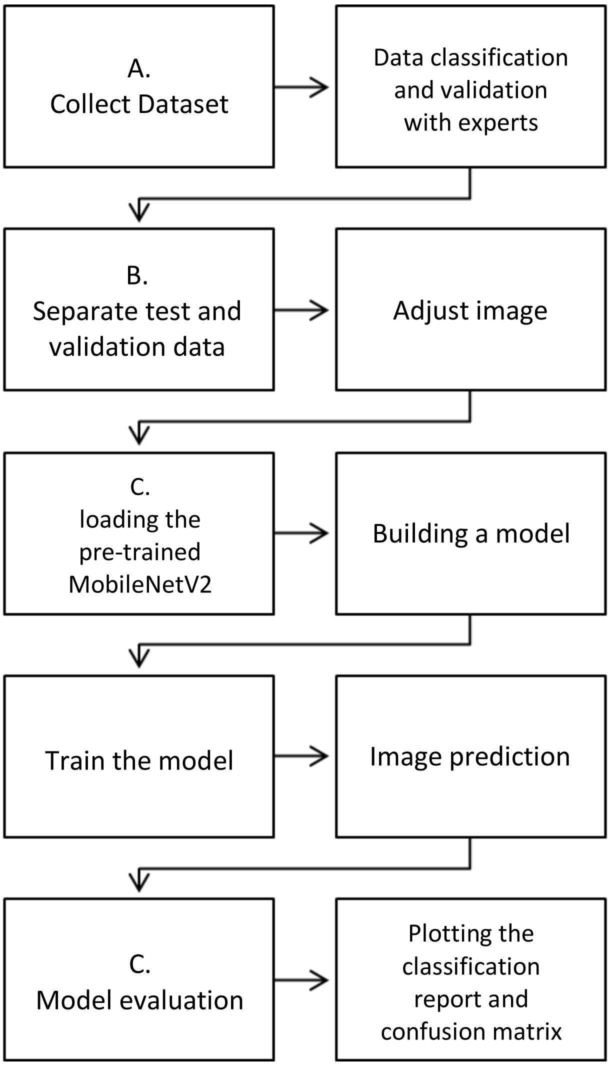

Figure 1. Research Stages

The image data equation needed in this study comes from a dataset contained in Kaggle [12] which contains 4 categories with a total of 4188 images. This dataset contains 4 categories, namely gray leaf spot (574 images), Common rust (1306 images), Blight (1146 images), and Healthy (1162 images). The researcher only took 4 categories in the existing dataset collection, namely the gray leaf spot category (574 images), Common rust (1306 images), Blight (1146 images), and Healthy (1162 images).

In front of Universitas Darussalam Gontor, researchers also took a direct picture of one of the rice fields. The image was taken on August 6, 2023 and taken on August 9, 2023 from 09:00 to 11:00 with very sunny weather. Data collection was carried out using the camera from the "Xperia 1" mobile phone. As for the shooting, the setting was carried out in ISO value of 64 and in the exposure time of 1/320s using the "Wide" lens size. The results obtained in the shooting amounted to 102 images with a resolution of 4032 x 2268, 24 Color Depth, and the resulting format was in the form of JPG. The data obtained had a similar type of disease, namely "Leaf Blight" (Bacterial Leaf Blight) and data on healthy leaves. At this stage, data collection is limited to one leaf for one image collected in each category. In each example, it can be seen in Figure 2 along with the grouping table of each category in the dataset in Table 1.


(a) (b) (c)

Figure 2. Affected Leaves by Leaf Blight (a), Leaf Rust (b), and Gray Leaf Spot (c)

Table 1. Data Grouping

No	Category	Sum
1	Common Rust	1306
2	Grey Leaf Spot	574
3	Bacterial Leaf Blight	1248
4	Health	1162
	Total	**4290**

After the data collection stage, 4188 photos representing 4 categories of Leaf Blight, Common Rust, Grey Leaf Spot and Healthy were acquired by the researchers using the Kaggle platform. After that, the dataset was uploaded to Kaggle and made available for use in this study. Once uploaded, the procedure proceeds to Pre-Processing, where the application checks the data by displaying images categorized by the grouping stage.

To examine and identify aspects of the condition to be investigated in more detail, the researchers also conducted field investigations. As a result, 102 photos were collected from the field. During data exploration, the program resizes the image to adjust the image pixels to the size that has been prepared from the MobileNetV2 model. This is so that the image looks correct and suitable for clarification at the testing and validation stages.

When the Pre-Processing stage has been carried out, the researcher proposes a model architecture for clarifying disease images in corn plants using Pre-Trained MobileNetV2 with the inputs used are images with 224 X 224 pixels, 3-dimensional Array (RGB) with Networks that have been trained by Imagenet. There are 17 blocks in this model, and each block has several layers, including an Expansion Layer, a Depthwise Convulution, and a Projection Layer. For the model, you can see in Figure 3.

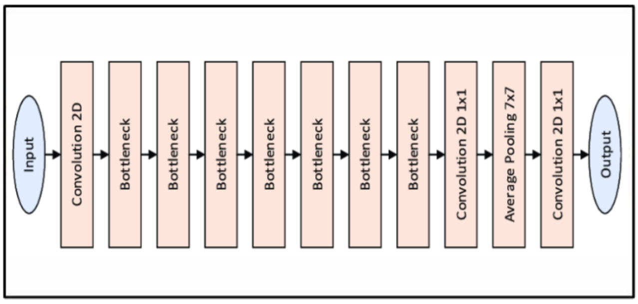

Figure 3. Architecture MobileNetV2

After going through the block of MobileNetV2, added Dense Layer 256 with Activation "Relu", Dense Layer is the same as before, 2 Layer Dropout 0.2 which is placed between Dense Layers and ends with Dense Layer with output consisting of 2 categories with Activation "Softmax". The parameters in Table 2 are the parameters that will be used in this study.

Table 2. Architecture Parameters of MobileNetV2

Parameter	Value
Bottleneck Residual	17
Activation Function	Relu, Softmax
Optimizer	Adam
Loss Function	Categorical Crossentropy
Epoch	50
Batch Size	64

One of the most prominent features is the pinnacle of the MobileNetV2 model, which is designed to classify images and create common features. Similar to MobileNetV1, but this model divides the convolution towards the base and towards the point. However, MobileNetV2 has two new features: Linear Bottleneck and Shortcut Connection. The model's inputs and outputs are at the bottleneck, while the inner layer, or inner layer, encapsulates the model's ability to change the input from a low concept to a high descriptor. Shortcuts between bottlenecks allow for faster and more accurate model teaching.

Batch Normalization is a technique used to improve exercise accuracy and reduce the risk of overfitting [13]. At the same time, the use of Dropout is applied in the classification of images in this study. The training optimization of this model uses Adam [14]. The use of Categorical Crossentropy in this study is to apply a function used to minimize loss and improve the accuracy of a model's performance. The following is the formula of Categorical Crossentropy.

$$H\,(P, Q) = -\sum_{\chi}^{X}(P(\chi)\log(Q(\chi))) \tag{1}$$

H = Cross-Entropy Function
P = Target Distribution
Q = Estimated Target Distribution

The researcher creates a Callback variable [15] to be used for model training. The Checkpoint Model function is used by the first callback at each epoch. This function saves the model in file form if the Val-Accuracy Matrix can increase during each epoch, and the model will not be accurate if the saved version of the model is inaccurate. The second callback stops the training process on the Val-Loss model that has not changed for 5 epochs, using the Early Stopping function of the same Library as the first callback. If used correctly, overfitting can be avoided [16].

Through the use of epochs, researchers conducted a research stage on the model. A total of 50 epochs from the dataset were used during the training process. The results of evaluation on test and validation data to show performance at the end of the training phase are the output of the model training process.

At this point, model evaluation is performed after training on the MobileNetV2 model. It includes the accuracy graph, the Loss graph, the Classification Report, and the Confusion Matrix obtained from the training epoch process. The Training Accuracy graph shows the accuracy of the model, and the Loss graph shows how much the model's performance degrades as it learns. An example of an Accuracy chart and a Loss chart can be seen in Figure 4.

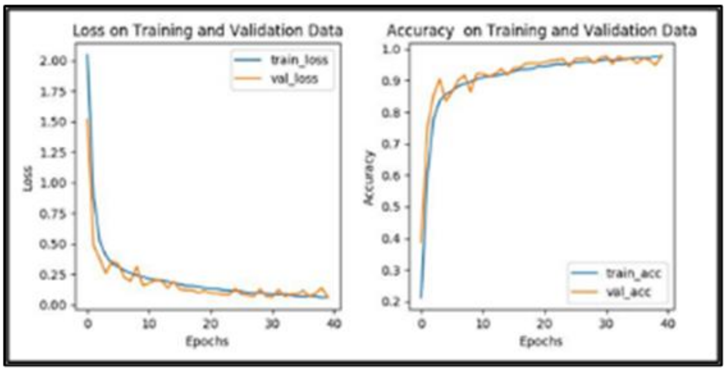

Figure 4. Example of a Graphic Image Accuracy and Loss

The performance of the model is evaluated by measuring the Confusion Matrix which is useful to see how many accurate predictions are made. Figure 5 shows an example of the Confusion Matrix [17].

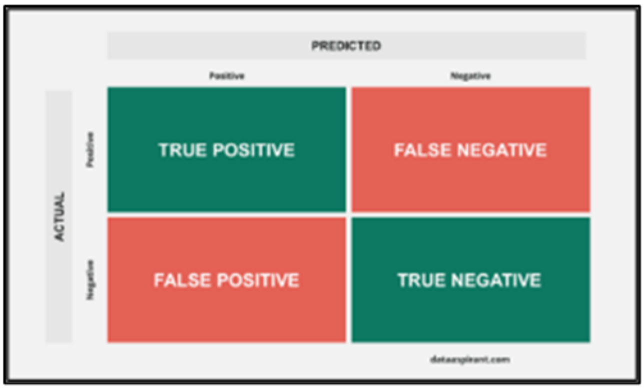

Figure 5. Confusion Matrix

In addition to the Confusion Matrix, the results of the evaluation are also seen through the classification report. This report shows how accurate the correct predictions are for the overall image of the dataset. If the number is below 1, then the model is considered to have good performance, and if the number is close to 0, then the opposite is stated. In the use of [18] Precision, Recall, and f1-score are applied to declare whether the model has good performance or not. Precision is a prediction that looks at the magnitude of the False Positive, where the greater the False negative, the smaller the recall performance. Meanwhile, Recall is a prediction that looks at the magnitude of False Negative. If the False Negative is enlarged, the Recall performance decreases. The f1-score is a combination of the quantity of Recall and Precision [19].

RESULTS AND DISCUSSION

Pre-Processing Stage

Each category i.e., diseased and healthy leaves has been grouped in the data that has been prepared. The data can now be uploaded to Kaggle and processed. Using this tool, the researchers examined the data to determine if it fell into the category they had. Figure 6 shows images that have been identified by category.

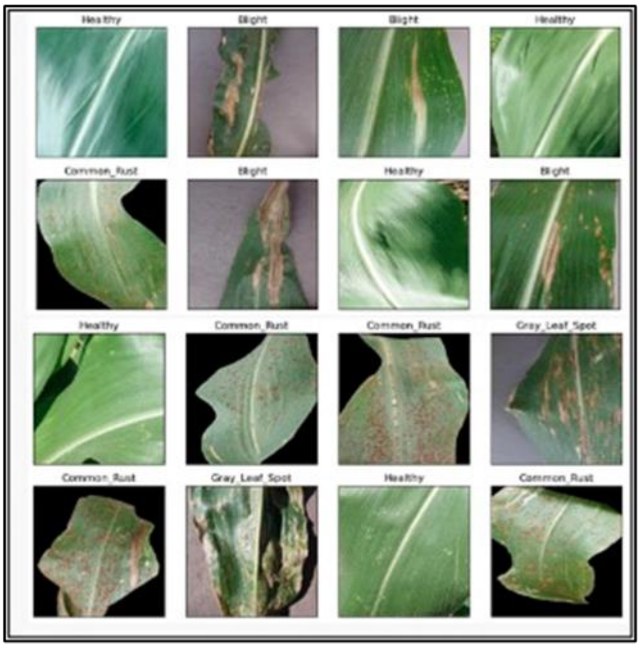

Figure 6. Results of Dataset Collection through Kaggle and Exploration

After the data was collected, the researcher divided the data into three types, namely training data (Train), test (Test), and validation (Validation) to meet the processing stage of image classification. Data distribution will be explained in table 3.

Table 3. Data Distribution

No	Data Name	Sum
1	Data Train	2746
2	Data Test	858
3	Data Validation	686

Once the data is divided, the image is ressized to 224 x 224 pixels. This method is used to match the size of the model MobileNet that has been studied before with the pixel size used in data collection. For dataset partitions, the researchers only received numbers that corresponded to the photos in the dataset.

The number for each category that has been processed by Kaggle is not provided. The purpose of the shift layer is to change the image value from [0 – 255] to the value [-1, 1] [20]. This is because the expected input of the MobileNetV2 model has a value of [-1, 1] for each pixel of the image.

Processing Stage

At this time, the donated P100 GPU is used to train the model on the Kaggle platform. This study uses corn leaves to develop a disease classification model. Using the parameters listed in Table 4, the MobileNetV2 Pre-Trained model architecture is used to perform the classification process.

The MobileNetV2 model uses 17 Residual Bottleneck blocks, which consist of several Layers, namely the Expansion Layer, Depthwise Convolution, and Projection Layer. After going through the MobileNetV2 block, a Dense Layer 256 with "relu" Activation is added. This is the same Dense Layer as before. Between the Dense Layer and the Dense Layer, there is a 2-layer dropout 0.2 positioned. Finally, there is a Dense Layer with Outputs that consists of two categories and has a "Softmax" activation. The image can be clarified by a categorization procedure that uses this model architecture. The deployment of the Checkpoint and Early Stopping Model callback variables during the 50-epoch training process is carried out to prevent the possibility of overfitting.

Table 4. Data Distribution with Parameters

No	Data Name	Health	Blight	Common Rust	Grey Leaf Spot	Total
1	Data Train	686	686	686	686	2744
2	Data Test	214	214	214	214	858
3	Data Validation	171	171	171	171	684

Trial and Validation Stage

With 50 epochs, the accuracy of the model test this time is quite good with 93.01%. However, the convergence process has not yet reached the final stage of the epoch in training. Figure 7 provides an explanation.

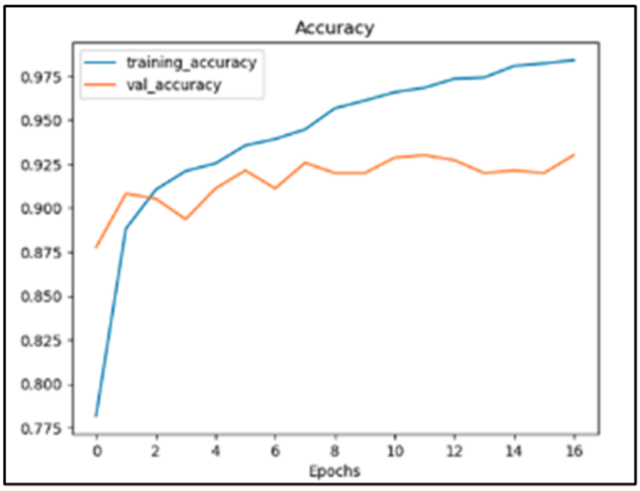

Figure 7. Graphic of Accuracy

The test results showed a loss value of 0.21940 with a range of values ranging from 0 to 1.2. An explanation can be seen in Figure 8.

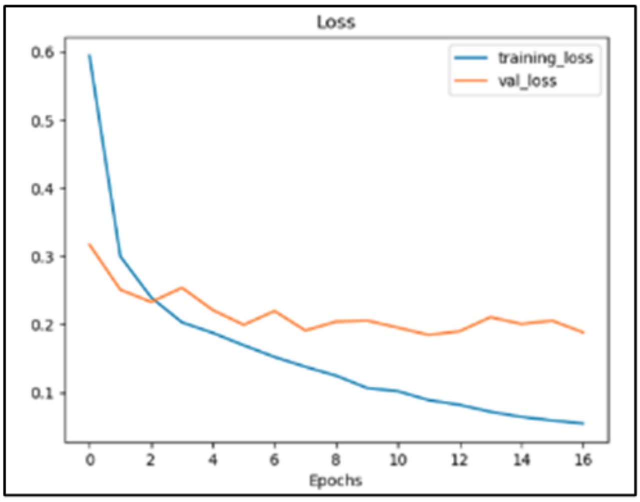

Figure 8. Graphic of Loss

Furthermore, the evaluation of the model is carried out by looking at the performance of the model displayed on the Confusion Matrix [21]. Figure 9 shows the results of the Confusion Matrix. The results showed that each category had good results.

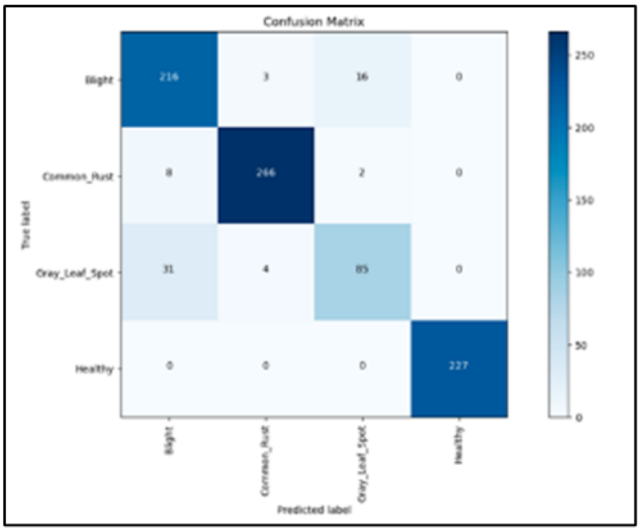

Figure 9. Confusion Matrix Results

The results of the model evaluation on Classification Report can be seen in Table 5. The overall accuracy is 0.925408. The determination of model performance is seen from the results of the graph Accuracy, Precision, Recall, and f1-Score [21]. The overall results of this Classification Report show that the leaf class affected by the disease Grey Leaf Spot received a lower value compared to other leaf classes, which was 0.825243 for Precision, 0.708333 to Recall, and 0.762332 for f1-score. Because the leaves affected by the disease Grey Leaf Spot has relatively little data compared to the other 3 categories.

Table 5. Classification Report

Category Name	Precision	Recall	F1-score
Blight	0.847059	0.919149	0.881633
Common Rust	0.974359	0.963768	0.969035
Grey Leaf Spot	0.825243	0.708333	0.762332
Healthy	1.000000	1.000000	1.000000
	Accuracy		**0.925408**

Furthermore, the MobileNetV2 model that has been pre-trained for the purpose of this study is randomly predicted in the image with a sequence of 4 predictions, namely healthy leaves and diseased leaves, and the results are shown in Figure 10.

Figure 10. Image Prediction Results Using MobileNetV2 Model

From Figure 10, the results of the image prediction using the MobileNetV2 To clarify the picture of disease on corn leaves has fulfilled the expected goal, which is to distinguish between pictures of healthy or healthy leaves and pictures of diseased leaves. However, it can be seen that some image prediction results still fail and do not match the actual category. It can also be seen in the 3rd column, 5th row that there are images exposed to sunlight in the collection of datasets in the field, so the results of the prediction state Blight.

CONCLUSIONS AND SUGGESTIONS

The MobileNetV2 model proved to be effective in clarifying diseases in corn leaves by reaching an accuracy value of 0.930070. However, there are some shortcomings, such as the convergent dagger model in the iteration process (epoch) on the data during the model training period and low in the healthy leaf category in the Classification Report.

In this study, the MobileNetV2 architectural model can work well on the image of diseased corn leaves. Researchers hope that this can lead to further development, especially related to the introduction according to each existing category. Further research is expected to use more categories and datasets to provide clarification on diseased leaves more comprehensively in maize leaves. With this, the benefits of the research results can be felt by farmers and the wider community by applying an artificial intelligence architecture model that can clarify the image on corn leaves.

BIBLIOGRAPHY

[1] R. M. Pikahulan, “Konsep Alih Teknologi Dalam Penanaman Modal di Indonesia Bidang Industri Otomotif,” *J. Cakrawala Huk.*, vol. 13, no. 2, 2017.

[2] Y. Yuwariah, D. Ruswandi, and A. W. Irwan, "Pengaruh Pola Tanam Tumpangsari Jagung dan Kedelai Terhadap Pertumbuhan dan Hasil Jagung Hibrida dan Evaluasi Tumpangsari di Arjasari Kabupaten Bandung," *Cultivation*, vol. 16, no. 3, pp. 514–521, 2018, doi: 10.24198/cultivation.v16i3.14377.

[3] W. Girsang, J. Purba, and S. Daulay, “Uji Aplikasi Agens Hayati Tribac Mengendalikan Pathogen Hawar DauN (Helminthosporium sp.) Tanaman Jagung (Zea mays L.),” *Jurnal Ilmiah Pertanian*, vol. 17, no. 1, pp. 51–59, Aug. 2020, doi: 10.31849/jip.v17i1.4614.

[4] M. Riswan, "Inventarisasi Hama dan Penyakit pada Pertanaman Jagung (Zea mays L.) di Desa Tumpatan Nibung Kecamatan Batang Kuis Kabupaten Deli Serdang," Skripsi, Univ. Medan Area, 2018, [Online]. Available: https://repositori.uma.ac.id/handle/123456789/9193

[5] L. O. S. Bande, G. Hs, and R. Resman, “Intensitas Penyakit yang Terdapat pada Tanaman Jagung dan Kacang Tanah dalam Pola Tumpangsari di Pertanian Lahan Kering Kabupaten Muna Barat,” *Pros. Semin. Nas. AGRIBISNIS*, Mar. 2015, doi: 10.37149/3129.

[6] R. Suhendra, I. Juliwardi, and S. Sanusi, “Identifikasi dan Klasifikasi Penyakit Daun Jagung Menggunakan Support Vector Machine,” *J. Teknol. Inf.*, vol. 1, no. 1, Art. no. 1, May 2022, doi: 10.35308/.v1i1.5520.

[7] I. P. Putra and D. Alamsyah, “Klasifikasi Penyakit Daun Jagung Menggunakan Metode Convolutional Neural Network,” *Jurnal Algoritme*, vol. 2, no. 2, pp. 102–112, 2022.

[8] R. Indraswari, R. Rokhana, and W. Herulambang, “Melanoma image classification based on MobileNetV2 network,” *Procedia Comput Sci*, vol. 197, pp. 198–207, 2021, doi: 10.1016/j.procs.2021.12.132.

[9] M. Toğaçar, Z. Cömert, and B. Ergen, “Intelligent skin cancer detection applying autoencoder, MobileNetV2 and spiking neural networks,” *Chaos Solitons Fractals*, vol. 144, p. 110714, Mar. 2021, doi: 10.1016/J.CHAOS.2021.110714.

[10] E. I. Haksoro and A. Setiawan, “Pengenalan Jamur yang Dapat Dikonsumsi Menggunakan Metode Transfer Learning pada Convolutional Neural Network,” *Jurnal ELTIKOM*, vol. 5, no. 2, pp. 81–91, 2021, doi: 10.31961/eltikom.v5i2.428.

[11] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, “MobileNetV2: Inverted Residuals and Linear Bottlenecks,” *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 4510–4520, 2018, doi: 10.1109/CVPR.2018.00474.

[12] G. Geetharamani and J. A. Pandian, “Identification of plant leaf diseases using a nine-layer deep convolutional neural network,” *Computers and Electrical Engineering*, vol. 76, pp. 323–338, 2019, doi: 10.1016/j.compeleceng.2019.04.011.

[13] K. Thenmozhi and U. S. Reddy, “Crop pest classification based on deep convolutional neural network and transfer learning,” *Comput Electron Agric*, vol. 164, p. 104906, 2019, doi: 10.1016/j.compag.2019.104906.

[14] D. Irfan, R. Rosnelly, M. Wahyuni, J. T. Samudra, and A. Rangga, "Perbandingan Optimasi SGD, Adadelta, dan Adam dalam Klasifikasi Hydrangea Menggunakan CNN," *J. Sci. Soc. Res.*, vol. 5, no. 2, Art. no. 2, Jun. 2022, doi: 10.54314/jssr.v5i2.789.

[15] D. Iswantoro and D. Handayani UN, "Klasifikasi Penyakit Tanaman Jagung Menggunakan Metode Convolutional Neural Network (CNN)," *J. Ilm. Univ. Batanghari Jambi*, vol. 22, no. 2, Art. no. 2, Jul. 2022, doi: 10.33087/jiubj.v22i2.2065.

[16] T. Dietterich, "Overfitting and undercomputing in machine learning," *ACM Comput Surv*, vol. 27, no. 3, pp. 326–327, Sep. 1995, doi: 10.1145/212094.212114.

[17] K. Liao, M. R. Paulsen, J. F. Reid, B. C. Ni, and E. P. Bonifacio-Maghirang, "Corn Kernel Breakage Classification by Machine Vision Using a Neural Network Classifier," *Transactions of the ASAE*, vol. 36, no. 6, pp. 1949–1953, 1993, doi: 10.13031/2013.28547.

[18] Z. Huang, A. Qin, J. Lu, A. Menon, and J. Gao, "Grape Leaf Disease Detection and Classification Using Machine Learning," *2020 International Conferences on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData) and IEEE Congress on Cybermatics (Cybermatics)*, pp. 870–877, March 2020, doi: 10.1109/iThings-GreenCom-CPSCom-SmartData-Cybermatics50389.2020.00150.

[19] R. Mawarni, R. Wulanningrum, and R. Helilintar, "Implementasi Metode CNN Pada Klasifikasi Penyakit Jagung," *Pros. SEMNAS INOTEK Semin. Nas. Inov. Teknol.*, vol. 7, no. 3, Art. no. 3, Jul. 2023, doi: 10.29407/inotek.v7i3.3566.

[20] T A. A. Y. Hakim and W. E. Pujianto, "Implementasi Teknologi Informasi Pada Komunikasi Organisasi Kepengurusan Pondok Pesantren Al-Hidayah Ketegan Tanggulangin," *MASMAN Master Manaj.*, vol. 2, no. 1, Art. no. 1, 2024, doi: 10.59603/masman.v2i1.263.

[21] H. S. Kaduhm and H. M. Abduljabbar, "Studying the Classification of Texture Images by K-Means of Co-Occurrence Matrix and Confusion Matrix," *Ibn AL-Haitham Journal For Pure and Applied Sciences*, vol. 36, no. 1, pp. 113–122, 2023, doi: 10.30526/36.1.2894.