Potato Leaf Disease Detection Using Image Processing with Transfer Learning

M. Turnip, E. Indra, D. Sitanggang, A. Situmorang, Ruben, D. R. H. Sitompul

***Abstract*— According to the Indonesia Central Bureau of Statistics, the province of North Sumatra produced about 1309976 tons of potato in 2019-2020. Limitation of farmers to detect plant diseases may cause crop failure. Plant diseases commonly found in potato leaves, such as late blight and early blight, might affect the quality of the potatoes. Early detection of leaf diseases can help farmers prevent further plant damage. This research presents a Convolutional Neural Network model with ResNet-50 architecture that can do image processing with a minimum accuracy of 85%. The Dataset used in this research was from Plant Village, which contains 2152 images and is classified to each disease. This research achieved the model accuracy of 98.4%, according to trials done.**

***Index Terms*— CNN, Image Processing, ResNet-50, Leaf Disease, Potato**

I. Introduction

IN this globalization era, technological advancement was so fast that technological influence's entry into all sector fields proved this. However, the influence is not yet embraced by the ordinary farmer. For example, detecting potato leaf diseases is still done with naked-eye observation, which requires an expert to do it, and this might cause much expense if the method is applied in large-scale farming [1]. With the help of an application that can detect leaf diseases, farmer jobs can be easier because they do not require expert help.

Similar research on leaf disease detection was done many times before; some of them are "Image Processing for Smart Farming: Detection of Disease and Fruit Grading" and "Plant Disease Detection Using Image Processing" [2-7]. These two research discuss leaf disease detection with experimental evaluation and statistics regression process, and then segmentation with K-Means Clustering was done. This method can only detect diseases based on color grading. The first step of their method is to transform Red, Green, Blue (RGB) into Hue, Saturation, Value (HSV), and then texture feature extraction is done with Gray Level Co-Occurrence Matrix (GLCM). The output will be classified with the Support Vector Machine (SVM) algorithm. The advantage of the mentioned research is predicting the leaf disease with an expert system.

According to previous research mentioned earlier, to reduce farmer mobility when detecting leaf disease, the writer proposes using a method that starts with collecting dataset from PlantVillage repository in Kaggle [4], then doing a test & train split on the dataset. Pre-processing will be done after that. Pre-processing covers resize & rescaling the picture, rotating the picture by 35°, and adjusting the picture saturation to get more features from a single picture (Data Augmentation). After that, a Convolutional Neural Network model will be built using ResNet-50 architecture, which is expected to have 85% of minimum accuracy. The difference of our method with the previous research is that we let the machine learn itself to predict the disease, not using an expert system.

II. Method

The research was done in the laboratory of Universitas Prima Indonesia. We use Google Colaboratory to train the model and using Google's GPU to boost the performance. The proposed method for identifying leaf disease in potato plan is shown in Fig 1; there are five main stages. The first one is getting the dataset from PlantVillage Dataset in Kaggle using the TensorFlow dataset (tf.dataset). Preprocessing stage comes in after that. In this stage, the data will be resized & rescaled and augmented. Data augmentation is done to extract more features from one image. The last stage is when the CNN model will be made.

A. Data Acquisition

The dataset used in this research came from the PlantVillage repository on Kaggle. PlantVillage consists of 14 kinds of plants with 38 categories of diseases. This research aims to identify potato leaf disease; therefore, only potato leaves were selected from this dataset. This dataset lists three categories of potato leaf disease, and Fig. 2 lists some of them. Except for the healthy leaves, there are only two disease categories for the potato plant: early blight and e blight. In this research, there are 2152 images collected in our dataset; 1000 of them are early blight, another 1000 are late blight, and the remaining 152 are healthy leaves. The details of the dataset can be seen in Table I.

B. Resize & Rescale

In this research, images that have already been split into train & tests will be resized and rescaled. This method will be helpful when predicting leaf disease from images outside the testing dataset. The original images will be resized & rescaled to a fixed resolution to improve memory storage capacity and reduce computational complexity. The resize & rescale method will reduce all image input to the dimension of 256 x 256 pixels [9]. Resize & rescale processes can be seen in Fig.

3.

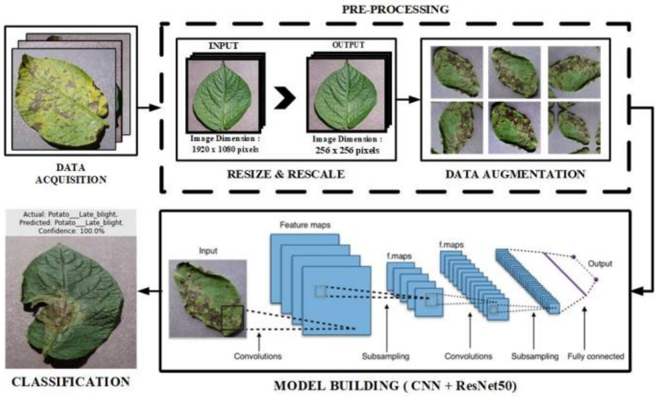
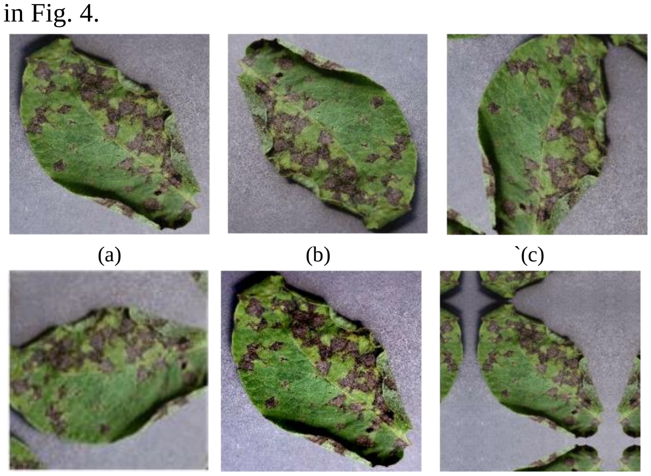


Fig. 1. Project's Workflow

C. Data Augmentation

Data augmentation is used for extracting more features from an image [10]. In this research, only the train dataset will get this method. Data augmentation has four steps: Flipping the image vertically and horizontally, rotating the image by 35°, adjusting the image contrast higher/lower, and adjusting the image zoom. The four steps of data augmentation can be seen in Fig. 4.



(a) (b) \`(c)

(d) (e) (f)

Fig. **2**. Augmented Potato Leaves: (a) Normal Image, (b) Image Flipped, (c) Image Rotation I, (d) Image Rotation II, (e) Image Saturation Adjustment, (f) Image Zoom Adjustment

D. Model Building

1) Convolutional Neural Network (CNN)

This research uses CNN for its model building. CNN is the standard algorithm used for image processing. The proposed CNN architecture in this research is ResNet-50; it has deep layers to get every image's features and increase the model accuracy.

Convolutional Neural Network is one class from deep learning that can perform image recognition and classification. The Convolutional Neural Network method is a class of neural networks specializing in processing data with a grid-like topology, such as images. The Convolutional Neural Network method can be used in face recognition, document analysis, image classification, video classification.

2) ResNet50

Resnet50 architecture consists of two sub-blocks: convolution block and identity block. Convolution block contains convolution-2D, batch normalization, and activation function that is ReLU. Then, it gave the input to a convolution and batch normalization, which will add the output. Finally, the activation function will get it all. Identity block contains an activation function, batch normalization, and convolution, then the input is added to the obtained output, and the activation function will have it. The architecture follows the sequence of convolution blocks and identity blocks as per requirement. It involves max-pooling, zero padding, average pooling connected to the flatten layer, and we will get the output image from the fully connected layer [11,21]. The proposed architecture design and its parameters can be seen in Fig. 3 & 4.

Bottleneck structure is a residual module in the Resnet-50 network model. Short-cut structures, also known as direct connection channels, have been introduced to the network, allowing a portion of the preceding network layer's output to be kept. This simple change to the network adds no additional parameters or computations, but it can significantly improve the model's training pace and training effect. This structure can address the problem so well that the gradient vanishes during back propagation as the network grows deeper.

The network's default image input size is 224x224. The first layer's convolution kernel size is 77%, which extracts the images' fundamental properties. The features are subsequently stored in the bottleneck residual block structure to extract higher-level features. Each convolutional layer is followed by a Batch Normalization layer and a ReLU function to boost convergence speed. Each hidden layer undergoes data batch normalization. This eliminates the issue of different distributions between testing and training images and makes each layer network relatively self-contained. To calculate the loss function, the data at the end of the network structure translates the output results to the interval of (0, 1) using the Softmax function.

The loss function is made up of numerous elements in most cases. The cross-entropy function is the most widely utilized error cost for classification issues. In reality, the L2 regularization term is frequently included in the training procedure to avoid over-fitting. The loss function is described as follows:

$$f(x)_1 = \frac{e^{x_1}}{\sum_j e^{x_j}}, \tag{1}$$

$$Loss(x, y, w) = -\sum_{i=1}^{n} yi \log f(x)_i + \lambda \|w\|_2^2 \tag{2}$$

where $f(x)_i$ is the i-th actual output probability in the classification vector after the Softmax function, which means the i-th actual output probability. The predicted output probability is y_i, while the Regularization factor is λ.

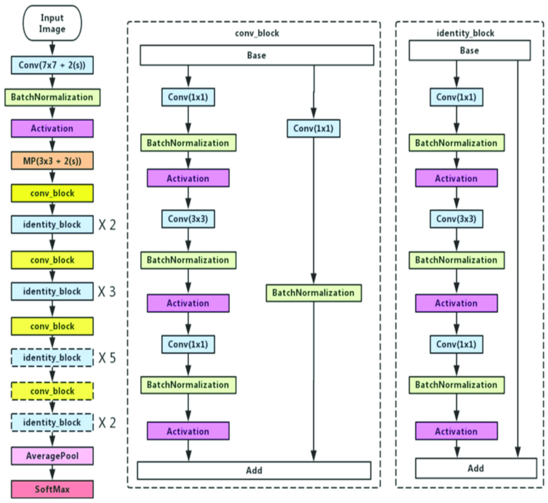


Fig. 3. Proposed CNN Model Architecture Using ResNet-50
Source: [13]

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
resnet50 (Model)             (None, 1, 1, 2048)        23587712
_________________________________________________________________
flatten_1 (Flatten)          (None, 2048)              0
_________________________________________________________________
dense_1 (Dense)              (None, 1024)              2098176
_________________________________________________________________
dense_2 (Dense)              (None, 512)               524800
_________________________________________________________________
dropout_1 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_3 (Dense)              (None, 256)               131328
_________________________________________________________________
dropout_2 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_4 (Dense)              (None, 128)               32896
_________________________________________________________________
dropout_3 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_5 (Dense)              (None, 10)                1290
=================================================================
Total params: 26,376,202
Trainable params: 26,323,082
Non-trainable params: 53,120
_________________________________________________________________
```

Fig. **4**. Proposed Model Including ResNet50

III. Result and Discussion

After the pre-processing stage and the built model, we come to the evaluation part. This part will present the result of accuracy & loss and prediction. The model training process will be shown in Table 1.

TABLE I
TRAINING PROCESS

EPOCH	Training		Testing	
	Accuracy	*Loss*	*Accuracy*	*Loss*
1	0.4457	1.3338	0.7546	0.8415
2	0.5561	0.9261	0.7685	0.6392
3	0.6787	0.7636	0.7361	0.7016
4	0.7507	0.6568	0.8102	0.5473
5	0.7763	0.6258	0.8148	0.4864
6	0.7780	0.6454	0.6991	0.8474
7	0.7676	0.6088	0.6991	0.8474
8	0.7868	0.6051	0.8102	0.6372
9	0.7908	0.5866	0.7824	0.6061
10	0.7914	0.6023	0.8287	0.4746
…	…	…	…	…
50	0.8536	0.4444	0.8380	0.4792

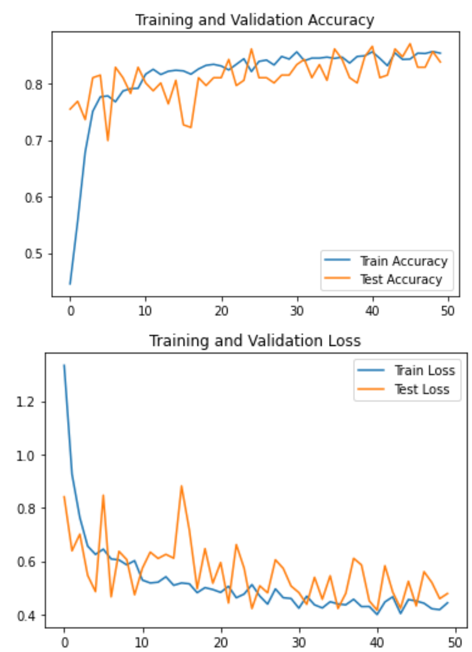
A. *Accuracy & Lost Result*

We see that the model we built was robust (not overfitting). The training-validation accuracy and the loss were close; also, the model accuracy is 86.51% (Fig. 5). The plot for the model training progress is shown in Fig. 6.

```
[ ] scores = model.evaluate(valid_set)

7/7 [==============================] - 19s 3s/step - loss: 0.4137 - accuracy: 0.8651
```

Fig. **5**. Model Accuracy



(a) (b)
Fig. **6**. Training Progress Plot : (a) Training & Validation Accuracy and Loss

B. *Prediction Result*

The validation dataset will predict the potato leaf disease, which was all images that the model has not touched. The prediction will show the actual category, the predicted category, and how much confidence the machine predicted the images

In this research, the prediction will be made to batches of images from the validation dataset—the preview of how prediction is made is shown in Fig 7, the prediction result will be shown in Table 2 and confusion matrix in Fig. 8.

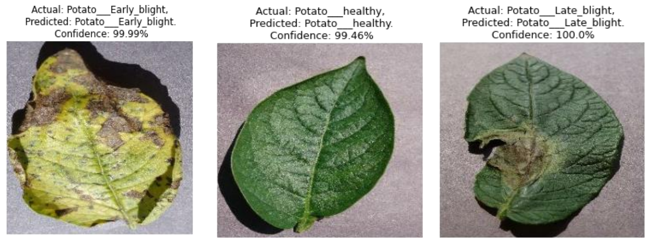


Fig. **7**. Leaf Disease Classification

C. Comparison with Previous Research

The comparison of this research model's accuracy and the previous research accuracy can be seen in Table III.

As shown in Table III, the average model accuracy score is 92,816%; this concludes that our model has more score on the model accuracy than the mentioned previous research.

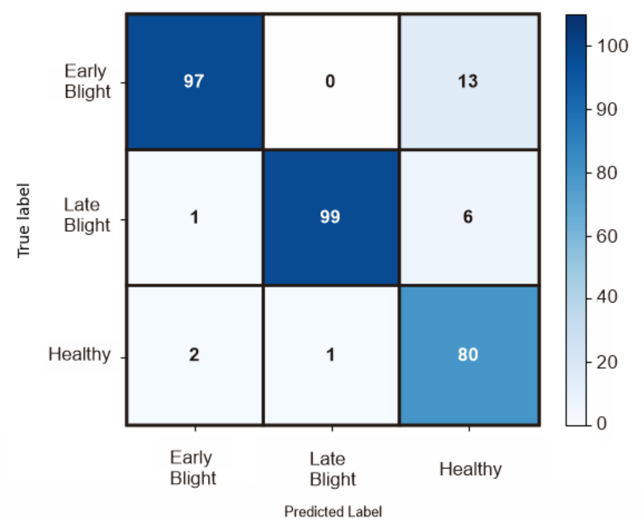


Fig. **8**. Confusion Matrix of the Result

TABLE II
RESEARCH COMPARISON

Research	Precision	Method
[2]	90%	Artificial Neural Network
[3]	91,6%	K-Means & Artificial Neural Network
[4]	94,7%	Support Vector Machine & Artificial Neural Network
[5]	94,6	Support Vector Machine
[6]	90%	Support Vector Machine, K-Means and Artificial Neural Network
[7]	96%	K-Means and Support Vector Machine
This Research	96,7%	Convolutional Neural Network with ResNet-50 Architecture

IV. CONCLUSION

This research concludes that we got a good result from the model building, which is not overfitting. The model is not overfitting because, as we can see in the model training plot (Fig. 6), the training-validation accuracy and loss were not separated so far, but they were tied close. The model also got 98.4% accuracy, which by standard means the model can be used for farmers to detect leaf diseases precisely with a minimum margin of error. This research also surpasses the target of getting at least 80% correct prediction in model testing. The benefit we got from this research is that we obtained experience in preventing more damage in a plant by diagnosing the leaf disease earlier.

ACKNOWLEDGMENT

This research is fully supported by the program study of Information System in Universitas Prima Indonesia. Huge appreciation to the Dean of Faculty of Technology and Computer Science, Mr. Mardi Turnip, our adviser, and the Head of Information System Program Study, Mr. Evta Indra, who oversaw and advised us in this project, and also to all friends (senior and junior) who participate in our project.

REFERENCES

[1] Horst. R, Westcott's Plant Disease Handbook (Seventh Edition), Netherlands : Springer (2008).

[2] M. Jhuria, A. Kumar, and R. Borse, "Image processing for smart farming: Detection of disease and fruit grading", IEEE Second International Conference on Image Information Processing (ICIIP2013), pp. 521-526, December 2013.

[3] Sachin D. Khirade, A.B. Patil, "Plant Disease Detection using Image Processing", IEEE, 2015.

[4] R.P. Narmadha and G. Arulvadivu, "Detection And Measurement of Paddy Leaf Disease Symptoms using Image Processing", International Conference on Computer Communication and Informatics (ICCCI), January 2017.

[5] R.M. Prakash, G.P. Sarashwathy, G. Ramalakshmi, K.H. Mangaleswari and T.Kaviya, "Detection of Leaf Diseases and Classification using Digital Image Processing", IEEE International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS), 2017.

[6] M.E. Pothen and M.L. Pai, "Detection of Rice Leaf Diseases Using Image Processing", IEEE International Conference on Computing Methodologies and Communication (ICCMC 2020), 2020.

[7] Y.M. Oo and N.C. Htun, "Plant Leaf Disease Detection and Classification using Image Processing", International Journal of Research and Engineering, vol. 5, no. 9, pp. 516-523, September-October 2019.

[8] Chitali G. Dahaware, K.H. Wanjale, "A Modern Approach for Plant Leaf Disease Classification which Depends on Leaf Image Processing", International Conference on Computer Communication and Informatics (ICCCI), January 2017.

[9] M.N. Abu Bakar, A.H. Abdullah, N. Abdul Rahim, H. Yazid, S.N. Misman and M.J. Masnan, "Rice Leaf Blast Disease Detection Using MultiLevel Colour Image Thresholding", Journal of Telecommunication, Electronic and Computer Engineering, vol. 10, no. 1-15, pp. 1-6, 2018.

[10] M. Agnieszka, G. Michal, "Data augmentation for improving deep learning in image classification problem", IEEE 2018 international interdisciplinary Ph.D. Workshop, 2018.

[11] I. Syed, M.S. Kumar, M.V.D. Prasad, N.T.B.S Sai, R.U.S. Lakshmi, P.P.K. Reddy and M.T.K. Kumar, "Leaf Disease Detection Using ResNet50", International Journal of Advanced Science and Technology, vol.29, no.4, pp.4816-4824, 2020.

[12] J. Naranjo-Torres, M. Mora, R. Hernández-García, R. J. Barrientos, C. Fredes, and A. Valenzuela, "A Review of Convolutional Neural Network Applied to Fruit Image Processing," Applied Sciences, vol. 10, no. 10, p. 3443, May 2020.

[13] A. Waheed, M. Goyal, D. Gupta, A. Khanna, A. E. Hassanien, and H. M. Pandey, "An optimized dense convolutional neural network model for disease recognition and classification in Corn Leaf," Computers and Electronics in Agriculture, vol. 175, p. 105456, 2020.

[14] Q. Yan, B. Yang, W. Wang, B. Wang, P. Chen, and J. Zhang, "Apple leaf diseases recognition based on an improved convolutional neural network," *Sensors*, vol. 20, no. 12, p. 3535, 2020.

[15] M. Syarief and W. Setiawan, "Convolutional neural network for maize leaf disease image classification," TELKOMNIKA (Telecommunication Computing Electronics and Control), vol. 18, no. 3, p. 1376, 2020.

[16] S. Mishra, R. Sachan, and D. Rajpal, "Deep convolutional neural network based detection system for real-time corn plant disease recognition," Procedia Computer Science, vol. 167, pp. 2003–2010, 2020.

[17] S. Baranwal, S. Khandelwal, and A. Arora, "Deep learning convolutional neural network for Apple leaves disease detection," SSRN Electronic Journal, 2019.

[18] I. Ahmad, M. Hamid, S. Yousaf, S. T. Shah, and M. O. Ahmad, "Optimizing pretrained convolutional neural networks for tomato leaf disease detection," Complexity, vol. 2020, pp. 1–6, 2020.

[19] M. Agarwal, A. Sinha, S. K. Gupta, D. Mishra, and R. Mishra, "Potato crop disease classification using convolutional neural network," Smart Systems and IoT: Innovations in Computing, pp. 391–400, 2019.

[20] Q. Ji, J. Huang, W. He, and Y. Sun, "Optimized Deep Convolutional Neural Networks for Identification of Macular Diseases from Optical Coherence Tomography Images," Algorithms, vol. 12, no. 3, p. 51, Feb.2019.

[21] Turnip, A., Andrian, Turnip, M., Dharma, A., Paninsari, D., Nababan, T., Ginting, C.N., An application of modified filter algorithm fetal electrocardiogram signals with various subjects, International Journal of Artificial Intelligence, vol. 18, no., 2020.

[22] D. Sitanggang, S. D. Siregar, S. M. F. Situmeang, E. Indra, A. R. Sagala, O. Sihombing, M. Nababan, H. Pasaribu, R. R. Damanik, M. Turnip, and R. I. E. Saragih, "Application of forwardchaining method to diagnosis of Onion Plant Diseases," *Journal of Physics: Conference Series*, vol. 1007, p. 012048, 2018.

[23] D. E. Kusumandari, M. Adzkia, S. P. Gultom, M. Turnip, and A. Turnip, "Detection of strawberry plant disease based on leaf spot using color segmentation," *Journal of Physics: Conference Series*, vol. 1230, no. 1, p. 012092, 2019

Mardi Turnip received S.Kom. degree in Informatics Engineering from the National Institute of Technology (ITENAS) Bandung, Indonesia, in 2010 and the M.Kom degree. in the Information System from STMIK LIKMI Bandung, Indonesia, in 2013. He worked at Universitas Prima Indonesia, Indonesia as a lecturer. The research area is information systems and artificial intelligence.

Evta Indra is currently the Chair of the Information Systems Study Program, Faculty of Technology and Computer Science, Universitas Prima Indonesia. and also currently the Editor in Chief of Jurnal Sistem Informasi dan Ilmu Komputer PRIMA (JUSIKOM PRIMA). Received a Bachelor's Degree in Computers in 2012 at the Potential Utama University of Medan, and a Master's Degree in Computers in 2015 at UPI YPTK Padang. His research interests include decision support systems, expert systems, geographic information systems, artificial intelligence, data mining.