Early Detection of Potato Leaf Pest and Disease Using EfficientNet and ConvNeXt Architecture

Conference Paper · December 2023

DOI: 10.1109/CONMEDIA60526.2023.10428527

Irmawati Irmawati
Multimedia Nusantara University

Dinar Ajeng Kristiyanti
IPB University

Tika Adilah Mutiara
Bina Sarana Informatika

Nabila Husna Shabrina
Multimedia Nusantara University

2023 7th International Conference on New Media Studies
Bali, Indonesia, 6-8 December 2023

Early Detection of Potato Leaf Pest and Disease Using EfficientNet and ConvNeXt Architecture

Irmawati
Department of Information System
Universitas Multimedia Nusantara
Tangerang 15111, Banten, Indonesia
irmawati@umn.ac.id

Dinar Ajeng Kristiyanti
Department of Information System
Universitas Multimedia Nusantara
Tangerang 15111, Banten, Indonesia
dinar.kristiyanti@umn.ac.id

Tika Adilah M
Department of Information Technology
Universitas Bina Sarana Informatika
Jakarta Pusat 10450, Jakarta, Indonesia
tika.tam@bsi.ac.id

Nabila Husna Shabrina
Department of Computer Engineering
Universitas Multimedia Nusantara
Tangerang 15111, Banten, Indonesia
nabila.husna@umn.ac.id

Siwi Indarti
Department of Plant Protection
Universitas Gadjah Mada
Sleman 55281, Yogyakarta, Indonesia
siwi.indarti@itb.ac.id

Niki Prastomo
Department of Engineering Physics
Universitas Multimedia Nusantara
Tangerang 15111, Banten, Indonesia
niki.pratomo@umn.ac.id

2023 7th International Conference on New Media Studies (CONMEDIA) | 979-8-3503-0750-4/23/$31.00 ©2023 IEEE | DOI: 10.1109/CONMEDIA60526.2023.10428527

***Abstract*—Potato farming has problems in the form of diseases that often attack potato leaves. This disease can affect potato crop production and can even result in crop failure. Early detection is needed to help farmers decide to increase potato production quality. Disease detection models in potato leaf plants have been developed using the Convolutional Neural Network (CNN) algorithm. This research aims to develop a disease detection model on potato leaves using the EfficientNet and ConvNeXt methods and evaluate the effectiveness of these two models in classifying four types of potato plant leaf diseases and 1 type of healthy potato leaf. Augmentation techniques are used to overcome imbalanced data, and Transfer Learning (TL) methods such as EfficientNet and ConvNeXt architectures are used for classification. We evaluated the model resulting from the experimental results using performance measures of accuracy values. Based on our experiments, the final results show that the EfficientNet model for disease detection on potato leaves achieved a validation accuracy of 95.64% and a testing accuracy of 95.92%. Meanwhile, the ConvNeXt model's validation accuracy value was 95.44%, and the testing accuracy value was 94.29%.**

Keywords—convnext; convolutional neural network; efficientnet; potato leaf pest and diseases detection; transfer learning.

I. INTRODUCTION

Research in agriculture is crucial to support global food security. A critical aspect of agriculture is controlling plant disease, which can significantly reduce crop yields. Potatoes are an essential food crop because they can support a farmer's life. Currently, potatoes are the most important vegetable crop in the world that can be a substitute for wheat and rice as a food crop [1].

Potatoes are one of the leading food crops which are very susceptible to various diseases, including those caused by fungi, bacteria and viruses [2]. Diseases in potato plants are one of the main challenges in modern agriculture. One of the primary diseases that attacks potatoes is leaf blight, or what is usually called late blight, and other diseases on potato plants that are often found as dry spots (early blight). Potato leaf diseases can result in significant yield reductions and spread quickly if not detected early, yielding many losses. Therefore, developing methods for early detection of potato leaf diseases is essential to increase the productivity and sustainability of potato farming.

Currently, the approach for detecting and identifying plant diseases is a naked-eye observation by experts [3]. However, direct observation has several disadvantages, such as it is hard to recognize similarities between one type of disease and another, which impacts subjectivity. An approach that is developing rapidly in the early detection of plant diseases is using digital image processing technology [4]. The application of artificial intelligence, especially in the form of artificial neural networks, has expanded the boundaries of possibilities for detecting and identifying plant diseases with high accuracy [5]. The importance of detecting plant diseases at an early stage not only provides farmers with quicker information to take preventative action but can also reduce adverse economic and environmental impacts.

In recent years, artificial intelligence technology, especially in image processing, has become a potential solution to this problem. One approach is to use the EfficientNet or ConvNeXt architecture in the early detection of diseases in plants. EfficientNet is known for its high efficiency and scalability; developed using the Neural Architecture Search method, EfficientNet achieves excellent performance with a relatively low number of parameters [6], which makes it ideal for applications where computing resources are limited. ConvNeXt is also a prominent CNN architecture renowned for its ability to combine information from multiple viewing angles. By building complex connectivity between convolutional layers, ConvNeXt can capture better spatial information, which can help detect complex or irregular patterns [7].

Recent relevant research to this paper is the work of Ferentinos et al. [8] and Ren et al.[9]; these two studies provide valuable insights into the application of deep learning in plant disease detection and provide a theoretical basis for this research.

In this study, we designed a model for detecting leaf diseases in potato crops based on images from the researchers Sholihati et al. [10], using the EfficientNet and ConvNeXt architecture. By utilizing these two architectures, this research can significantly contribute to developing an automation system for monitoring leaf diseases in potato crops.

II. RELATED WORKED

The detection of plant diseases has garnered significant attention in agricultural research, with advancements in computer vision techniques providing valuable tools for accurate and timely diagnosis. In the potato plants, a crucial staple in many regions, the need for accurate and timely detection of leaf diseases is paramount.

Research on disease detection on potato leaves consists of various approaches. Machine learning approaches continue to develop and are often used by researchers and industry in several fields, such as image processing [11], computer vision [12] [13], speech recognition [14], face recognition [15], and natural language processing [16]. However, this approach still needs to be solved for feature engineering. With deep learning, it is possible to achieve significant results without performing feature engineering. Convolutional Neural Network (CNN) is a method that is a type of Deep Neural Network that is designed to process two-dimensional image data [17]. CNN combines three basic architectures, namely Local Connection, Shared Weight in the form of filters, and Spatial Subsampling in the form of Pooling [18][19].

There has been much research on potato leaf diseases, and we took several studies on the detection and classification of potato leaf diseases. M. Islam et al. [20] combined image processing and machine learning methods to automatically classify diseases on potato leaves. Their proposed approach is capable of classification with 95% accuracy. Sholihati et al. [10] identified potato diseases based on the condition of the leaves. The researchers classified four types of diseases in potato plants using the VGG16 and VGG19 architectures with accuracy results of 91%. The following researcher [21] carried out the detection of potato leaf disease based on three classes. The researcher created a CNN architecture with a total of 6.8 million parameters. The experimental results obtained a validation accuracy of 92%. Using the InceptionV3 model [22] identified two types of potato leaf diseases. The test accuracy results on the potato daub dataset were found to be 90%. However, in this study, there was a data imbalance where healthy data was much less than diseased leaves. The problem can be overcome by using the Augmentation technique; this technique is often used to deal with overfitting because it produces more training data. The goal of Augmentation is so that the model does not see the same image twice [23].

The innovation being developed in deep learning currently is the Transfer learning model, which is a method of using a neural network that has been previously trained and then reducing the number of parameters by taking several parts of the previously trained model to be used in recognizing new models [24][25]. F. Islam et al. [26] reported that transfer learning techniques can be used for early detection of potato diseases when it is difficult to collect thousands of images of new leaves. Transfer learning uses deep learning models to solve new problems.

Based on previous research, where many researchers used a dataset, namely "The Plant Village," which only consists of two types of disease, in this study, the author will use the dataset from the author [10]. The dataset is a combination of "The Plant Village," Google Images, and potato leaf disease images from the city of Malang, Indonesia. So, a more varied type of disease is obtained, namely four types of disease and one type of healthy leaf.

There needs to be more data on the healthy leaf, late blight, and early blight classes in the dataset. The problem caused by the use of not enough data is overfitting [27]. Therefore, in this research, we use data augmentation techniques to overcome data imbalance, use a transfer learning model to overcome the problem of small data and apply the transfer learning method of the EfficientNet and ConvNeXt architectures so that potato leaf disease detection can be carried out automatically.

III. Methodology

Our proposed research method consists of seven stages: data collection, pre-processing, split dataset, augmentation, image classifier, evaluation and predictive model. The general research workflow is shown in Fig. 1. The first stage is data collection, then data pre-processing and splitting the dataset into three parts: training data, validation and testing. The next stage is image augmentation, followed by an image classifier. The final stage is a predictive model using testing data to evaluate how well the predictive model was trained with the training set.

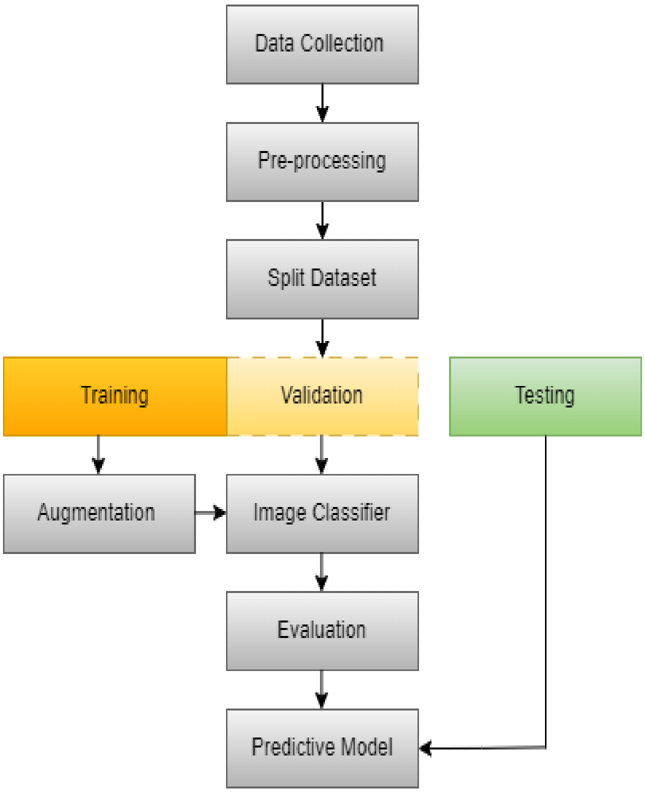
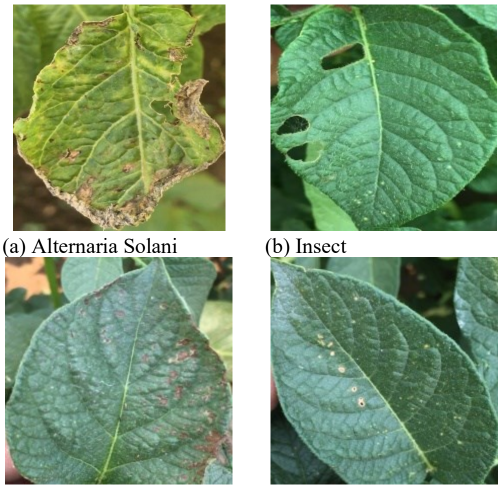


Fig.1. Block diagram of the proposed research methodology

A. *Data Collection and Pre-processing*

The dataset we use comes from three data sources: PlantVillage [28], Google Images and the results of the following author's [10] data collection from potato plantations in Malang, Indonesia. This data collection resulted in a dataset of 4.491 images divided into five classes: Alternaria solani, healthy, insects, viruses and phytophthora infestans. These datasets have varying sizes and image formats. Image format and size consistency are essential in deep learning because models require uniform input data to train effectively. Therefore, we resized all data to 224x224 in .jpg format.

After pre-processing, the dataset changed to 3,647 images from 4,491 images, divided into four types of potato leaf disease and one type of healthy leaf. The data composition of each kind is 1,055 Alternaria solani, 641 healthy, 261 insects, 694 viruses and 996 Phytophthora infestans. The appearance of the four types of disease on potato leaves that we use is shown in Fig. 2.



(a) Alternaria Solani (b) Insect

(c) Phytophthora Infestans (d) Virus

Fig.2. Examples of four types of potato leaf disease images in our dataset

B. Split Dataset

Dataset splitting by dividing data into subsets during model training, validation, and testing. The main goal of split datasets is to measure model performance and avoid overfitting objectively. In this condition, the model can memorize training data but not generalize to new data. In this study, we used a Python library called split-folders. Split folders provide simple but efficient functionality to divide the dataset into folders according to our needs. We take 10% of the data for testing data, and the rest is divided into 80:20 for training and validation data. Detailed distribution of the dataset can be seen in Table 1.

TABLE 1. THE RESULT OF SPLITTING DATASET

Class	Number of Dataset		
	Training	*Validation*	*Testing*
Alternaria Solani	664	285	106
Healthy	403	173	65
Insect	163	71	27
Virus	436	188	70
Phytophthora Infestans	627	269	100

C. Augmentation

Image augmentation techniques increase the amount and variety of training data by creating variations in existing images [29]. These techniques can improve model performance in understanding variations in real-world data. In detecting potato leaf disease, augmentation can increase the model's robustness to variations in lighting conditions, shooting angles, and leaf texture.

In this research, we performed data augmentation only on the training data set. It differs from the stage of preparing data using image resizing, which requires consistency across data sets that interact with the model. ImageDataGenerator is one of the functions in Keras as a neural networks API written in Python. In these EfficientNet and ConvNeXt architectures used, we perform random transformations on the training dataset using rotation, translation, and contrast techniques, then change the parameters in the function.

D. Image Classifier

The next stage is training the CNN model. Model training will be implemented using the transfer learning method. The CNN models that will be tested are several state-of-the-art models with high performance on the ImageNet [30] dataset: EfficientNet and ConvNeXt. The training will use the Python programming language using the Keras and Tensorflow libraries. During implementation, fine-tuning and optimising the training parameters will be carried out to optimise model performance. The architectures of the EfficientNet and ConvNeXT models are shown in Table 2 and Fig. 3. EfficientNet is an artificial neural network architecture designed to provide good performance on image recognition tasks with high parameter efficiency. Some parameters that can be optimized in EfficientNet involve factors such as depth, width and image resolution.

TABLE 2. EFFICIENTNET ARCHITECTURE [6]

Operator	Parameter		
	Resolution	*Channel*	*Total Layer*
Conv3x3	224x224	32	1
MBConv1, k3x3	112 x 112	16	1
MBConv6, k3x3	112 x 112	24	2
MBConv6, k5x5	56 x 56	40	2
MBConv6, k3x3	28 x 28	80	3
MBConv6, k5x5	14 x 14	112	3
MBConv6, k5x5	14 x 14	192	4
MBConv6, k3x3	7 x 7	320	1
Conv1x1 & Pooling & FC	7 x 7	1280	1

There are five variants of EfficientNet known as B0, B1, B2, B3, and B4. Each variant has a different level of efficiency. In this study, we used EfficientNetB0, the model with the smallest number of parameters compared to other variants; it has 5 million parameters. However, we used the trainable params only 1.1 million.

For feature extraction, we import the EfficientNet and ConvNeXt model from the Keras library. The imported model uses convolutional layers initialized with predefined weights and pre-trained using ImageNet. Furthermore, for classification, the Global Average Pooling layer and dense layer with SoftMax are added after the convolutional layer, not the fully connected layer. According to Lin et al. [32], fully connected layers are usually used in traditional CNN models and tend to overfit even when using dropout. Therefore, in this research, Global Average Pooling (GAP) is used, which enters the average value of each feature, maps it into a vector and links it to the input SoftMax layer directly.

In this research, we implemented the ConvNeXt-T architecture with the lowest number of parameters compared to other types of ConvNeXt. ConvNeXt-T has a total number of parameters of 29 million, and we use around 9.5 million as trainable parameters.

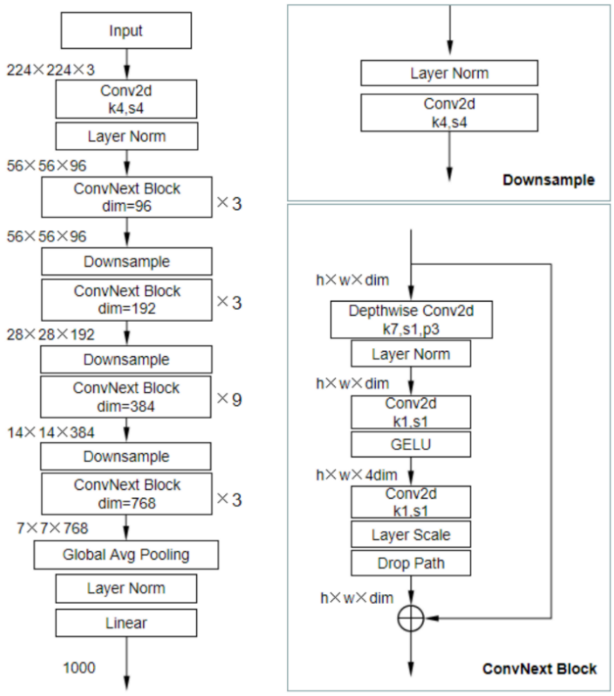


Fig.3. Architecture of ConvNeXt-T [31]

E. Evaluation

The performance results of the EfficientNet and ConvNeXt models for detecting leaf diseases in the potato crop will be evaluated using several metrics, such as accuracy and F1 score. The equation for each evaluation metric used in this research is shown in the following equation.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\Pr ecision = \frac{TP}{TP + FP} \tag{2}$$

$$\operatorname{Re} call = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - Score = \frac{2x \Pr ecision x \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call} \tag{4}$$

The model evaluation uses a test set to measure the accuracy, precision, recall, and F1-score for detecting leaf diseases in potato plants.

F. Predictive Model

Validation of a predictive model is necessary to ensure that the model can accurately predict the values of the variables of interest. The best model produced from the training dataset is tested using a testing dataset to measure the performance of the training model. We tested the model using a testing dataset of 368 images.

IV. RESULT AND DISCUSSION

To develop a model for potato leaf disease detection, we conducted experiments with the implementation of the EfficientNet and ConvNeXt architectures. We used the early stopping technique to determine the epoch value because our dataset is small. To handle overfitting causes of small datasets, we used early stopping, a regularization technique commonly used in training deep learning models to prevent overfitting and improve generalization performance. By using a batch size of 128, and a learning rate of 0.0001 to improve model performance.

In the training process, the model we implement tries to find values in the image dataset to recognize new images from our dataset. The result of the epoch will be recorded to determine loss value and accuracy. Loss indicates poor value in the model; the loss value obtained must be close to zero or equal to zero, and the accuracy value is a parameter for the model's success in classifying images. We use a loss plot to monitor how the model reduces prediction error over time. The resulting loss values using EfficientNet and ConvNeXt are presented in Fig. 4 and Fig. 5.

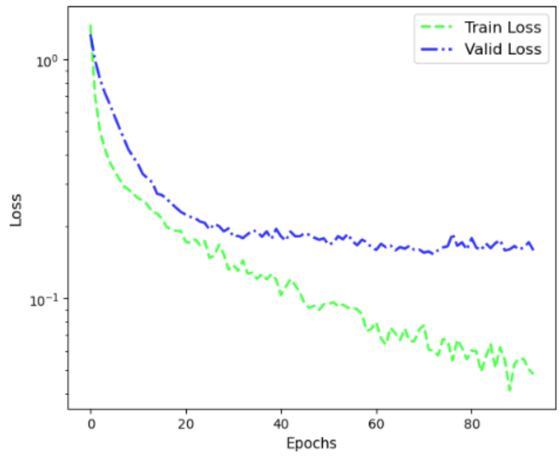


Fig.4. Training and validation loss of EfficientNet model

If we look at the plot in Fig. 4, the training loss is much smaller than the validation loss throughout the curve. The training loss's incoming curve is more stable than the validation loss in the validation phase. There are not too significant fluctuations in training loss and validation loss at the end of the curve. We can see that the training loss continues to decrease, but the validation loss tends to be stable; this indicates overfitting even though it is not very significant. We use earlystopping so the training process will stop after getting the optimal loss value.

In Fig. 5, the training loss graph decreases gradually over time, showing that the model learns from the training data well. There is no fluctuation in training loss and validation loss, but there is a significant difference between training and validation loss, so strategies must be considered to reduce overfitting.

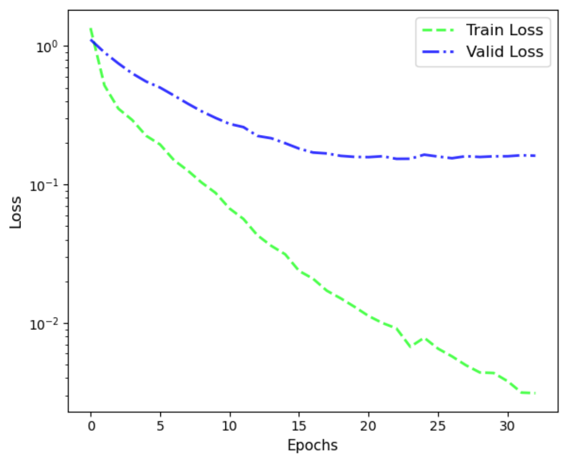


Fig.5. Training and validation loss of ConvNeXt model

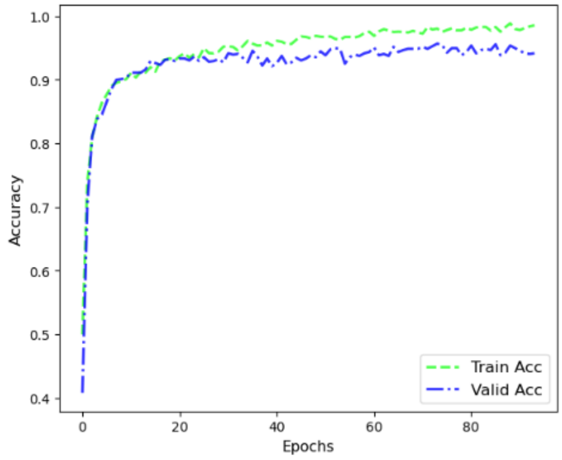


Fig.6. Training and validation accuracy of EfficientNet model

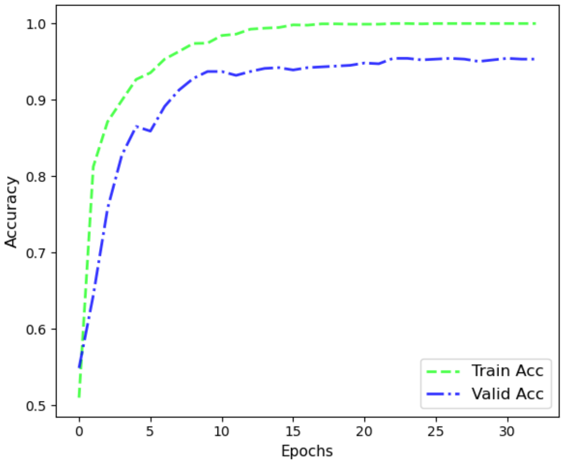


Fig.7. Training and validation accuracy of ConvNeXt model

Fig. 6 and Fig. 7 show graphs of accuracy values for the two architectures related to training. The graphic image shows the accuracy values on training and validation data over time or epoch. There is no large difference between training and validation accuracy on both architectures; this can indicate that overfitting does not occur. However, let's compare the curve shapes in the EfficientNet and ConvNeXt models. In EfficientNet, some fluctuations are insignificant, while in ConvNeXt, the curve shape tends to be stable without fluctuation. The resulting accuracy value based on the accuracy curve obtained a validation accuracy value for the EfficientNet model of 95.64% and 95.44% for the validation accuracy value for the ConvNeXt model. The EfficientNet model is 0.20% greater than the ConvNeXt model.

Apart from evaluating the results of the loss curve and accuracy in assessing the resulting model, we use evaluation with a confusion matrix using a testing dataset, which can provide a more detailed explanation of model performance than simple evaluation metrics such as accuracy.

Based on the confusion matrix results in Fig. 8, the accuracy value of the EfficientNet model test is 96%, with the best precision and recall values in the Alternaria Solani and Phytophthora classes of 0.99 for precision and 1.00 for recall. The best f1-score value is in the Alternaria Solani class, with a value of 1.00. This model can better identify Alternaria Solani classes because the amount of data in the Alternaria Solani class is greater than in other classes.

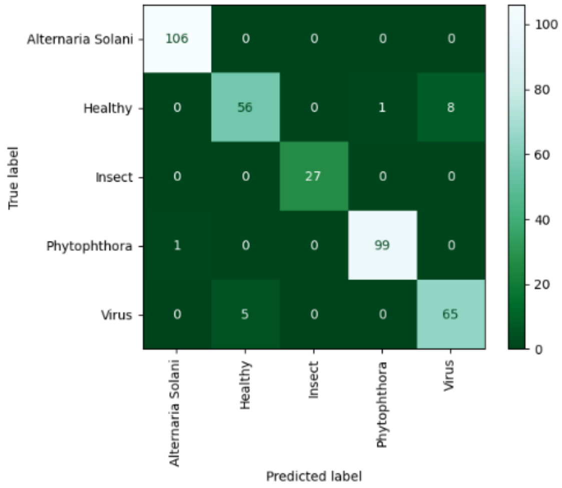


Fig.8. Confusion matrix of 368 testing images for EfficientNet

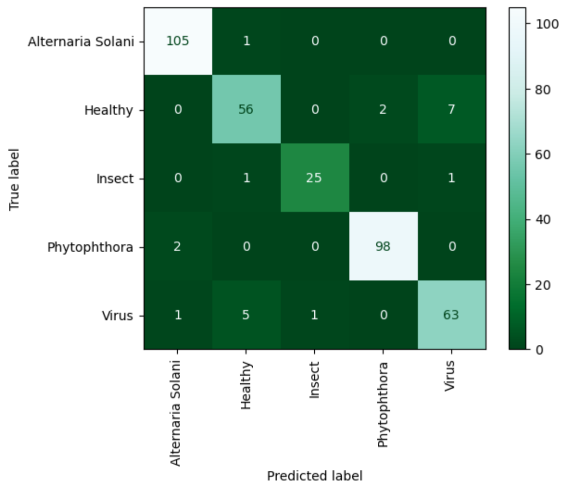


Fig.9. Confusion matrix of 368 testing images for ConvNeXt

The value of the confusion matrix results in the ConvNeXt model in Fig. 9 shows a model testing accuracy value of 94%, with the best precision value in the Phytophthora class of 0.98, the best recall value in the Alternaria Solani class with a value of 0.99. The best f1-score values are found in the Alternaria Solani and Phytophthora classes, with a value of 0.98.

Based on the performance evaluation results of the two models, it can be concluded that the EfficientNet model is superior for disease detection on potato plant leaves compared to the ConvNeXt model and several models from previous authors. Table 3 summarizes work related to the classification of potato leaf diseases.

TABLE 3. SUMMARY OF RELATED WORK ON POTATO LEAF DISEASE CLASSIFICATION.

Work	**Method**	**Accuracy [%]**		
		Training	***Validation***	***Testing***
[10]	VGG 16	-	91.00	91.31
	VGG19	-	91.00	90.96
Proposed	**EfficientNetB0**	**98.04**	**95.64**	**95.92**
	ConvNeXt-T	**100**	**95.44**	**94.29**

V. CONCLUSION

Based on the comparison table of model accuracy results for detecting leaf diseases in potato plants, currently, the EfficientNet and ConvNeXt models produce the best testing accuracy values, with a testing accuracy value on the EfficientNet model of 96% and a testing accuracy value on the ConvNext model of 94%. In future research, we will carry out optimization by providing regularization and dropout values to the two models to eliminate overfitting.

ACKNOWLEDGMENT

This study was financially supported by the Ministry of Research, Technology, and Higher Education of Indonesia in Fundamental Research Schemes (Grant number 1423/LL3/AL.04/2023). Authors would also like to thank Universitas Multimedia Nusantara for the support during this study.

REFERENCES

[1] S. Jansky, R. Navarre, and J. Bamberg, "Introduction to the Special Issue on the Nutritional Value of Potato," *Am. J. Potato Res.*, vol. 96, no. 2, pp. 95–97, 2019, doi: 10.1007/s12230-018-09708-1.

[2] J. E. Munyaneza and B. Bizimungu, "Management of potato pests and diseases in Africa," *Insect Pests of Potato*, pp. 407–426, 2022.

[3] S. Weizheng, W. Yachun, C. Zhanliang, and W. Hongda, "Grading method of leaf spot disease based on image processing," in *2008 international conference on computer science and software engineering*, 2008, vol. 6, pp. 491–494.

[4] T. N. Tete and S. Kamlu, "Plant Disease Detection Using Different Algorithms.," in *RICE*, 2017, pp. 103–106.

[5] I. Attri, L. K. Awasthi, T. P. Sharma, and P. Rathee, "A review of deep learning techniques used in agriculture," *Ecol. Inform.*, p. 102217, 2023.

[6] M. Tan and Q. Le, "Efficientnet: Rethinking model scaling for convolutional neural networks," in *International conference on machine learning*, 2019, pp. 6105–6114.

[7] Z. Liu, H. Mao, C. Y. Wu, C. Feichtenhofer, T. Darrell, and S. Xie, "A ConvNet for the 2020s," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. 2022-June, pp. 11966–11976, 2022, doi: 10.1109/CVPR52688.2022.01167.

[8] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Comput. Electron. Agric.*, vol. 145, pp. 311–318, 2018.

[9] C. Ren, D.-K. Kim, and D. Jeong, "A survey of deep learning in agriculture: Techniques and their applications," *J. Inf. Process. Syst.*, vol. 16, no. 5, pp. 1015–1033, 2020.

[10] R. A. Sholihati, I. A. Sulistijono, A. Risnumawan, and E. Kusumawati, "Potato Leaf Disease Classification Using Deep Learning Approach," *IES 2020 - Int. Electron. Symp. Role Auton. Intell. Syst. Hum. Life Comf.*, pp. 392–397, 2020, doi: 10.1109/IES50839.2020.9231784.

[11] A. S. Zamani *et al.*, "Performance of Machine Learning and Image Processing in Plant Leaf Disease Detection," *J. Food Qual.*, vol. 2022, pp. 1–7, 2022, doi: 10.1155/2022/1598796.

[12] A. S. A. Neto, A. R. Secchi, B. D. O. Capron, A. Rocha, L. N. Loureiro, and P. R. Ventura, "Development of a predictive emissions monitoring system using hybrid models with industrial data," in *Computer Aided Chemical Engineering*, vol. 51, Elsevier, 2022, pp. 1387–1392.

[13] N. H. Shabrina, R. A. Lika, and S. Indarti, "Deep learning models for automatic identification of plant-parasitic nematode," *Artif. Intell. Agric.*, vol. 7, pp. 1–12, 2023.

[14] S. Abro, S. Shaikh, Z. H. Khand, A. Zafar, S. Khan, and G. Mujtaba, "Automatic hate speech detection using machine learning: A comparative study," *Int. J. Adv. Comput. Sci. Appl.*, vol. 11, no. 8, 2020.

[15] F. Tabassum, M. I. Islam, R. T. Khan, and M. R. Amin, "Human face recognition with combination of DWT and machine learning," *J. King Saud Univ. Inf. Sci.*, vol. 34, no. 3, pp. 546–556, 2022.

[16] D. A. Kristiyanti and S. Hardani, "Sentiment Analysis of Public Acceptance of Covid-19 Vaccines Types in Indonesia using Naïve Bayes, Support Vector Machine, and Long Short-Term Memory (LSTM)," *J. RESTI (Rekayasa Sist. dan Teknol. Informasi)*, vol. 7, no. 3, pp. 722–732, 2023.

[17] D. H. Hubel and T. N. Wiesel, "Receptive fields and functional architecture of monkey striate cortex," *J. Physiol.*, vol. 195, no. 1, pp. 215–243, 1968.

[18] Y. Altuntaş, Z. Cömert, and A. F. Kocamaz, "Identification of haploid and diploid maize seeds using convolutional neural networks and a transfer learning approach," *Comput. Electron. Agric.*, vol. 163, p. 104874, 2019.

[19] Y. Yu, H. Lin, J. Meng, X. Wei, H. Guo, and Z. Zhao, "Deep transfer learning for modality classification of medical images," *Information*, vol. 8, no. 3, p. 91, 2017.

[20] M. Islam, A. Dinh, K. Wahid, and P. Bhowmik, "Detection of potato diseases using image segmentation and multiclass support vector machine," in *2017 IEEE 30th canadian conference on electrical and computer engineering (CCECE)*, 2017, pp. 1–4.

[21] G. Ri *et al.*, "Identification of Disease in Potato Leaves Using Convolutional Neural Network (CNN) Algorithm," *ICOIACT*, pp. 72–76, 2020.

[22] M. Turnip; E. Indra; D. Sitanggang; A. Situmorang; Ruben; D. R. H. SitompulI, "Potato Leaf Disease Detection Using Image," *Internetworking Indones. J.*, vol. 12, no. 2, pp. 25–29, 2020, [Online]. Available: http://www.internetworkingindonesia.org/Issues/Vol12-No2-2020/iij-vol12-no2-2020.html

[23] F. Chollet, *Deep Learning with Python*, vol. 10, no. 2. 2011. doi: 10.1016/s1474-4422(11)70007-2.

[24] M. Abas, N. Ismail, A. Yassin, and M. N. Taib, "VGG16 for Plant Image Classification with Transfer Learning and Data Augmentation," *Int. J. Eng. Technol.*, vol. 7, pp. 90–94, Oct. 2018, doi: 10.14419/ijet.v7i4.11.20781.

[25] K. Ramo, *Hands-On Java Deep Learning for Computer Vision*. 2019.

[26] F. Islam, M. N. Hoq, and C. M. Rahman, "Application of transfer learning to detect potato disease from leaf image," in *2019 IEEE International Conference on Robotics, Automation, Artificial-intelligence and Internet-of-Things (RAAICON)*, 2019, pp. 127–130.

[27] G. G. and A. P. J., "Identification of plant leaf diseases using a nine-layer deep convolutional neural network," *Comput. Electr. Eng.*, vol. 76, pp. 323–338, 2019, doi: https://doi.org/10.1016/j.compeleceng.2019.04.011.

[28] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Front. Plant Sci.*, vol. 7, p. 1419, 2016.

[29] A. Mikołajczyk and M. Grochowski, "Data augmentation for improving deep learning in image classification problem," in *2018 international interdisciplinary PhD workshop (IIPhDW)*, 2018, pp. 117–122.

[30] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, "Imagenet: A large-scale hierarchical image database," in *2009 IEEE conference on computer vision and pattern recognition*, 2009, pp. 248–255.

[31] Y. Wang, Y. Li, and H. Zou, "Masked Face Recognition System Based on Attention Mechanism," *Information*, vol. 14, no. 2. 2023. doi: 10.3390/info14020087.

[32] M. Lin, Q. Chen, and S. Yan, "Network in network," *arXiv Prepr. arXiv1312.4400*, 2013.