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Performance analysis of the application of convolutional neural networks architectures in the agricultural diagnosis

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ABSTRACT

Agriculture is an important sector for developing countries and farmers. Recently, numerous techniques for increasing agricultural productivity have been utilized. However, different issues are still encountered by farmers including various plant diseases. Plant diseases diagnoses are challenging research, and they should be analyzed and treated by detecting the diseased plant leaves. For that reason, in this paper, we develop our proposed architecture using convolutional neural networks (OP-CNN) as a computer-aided to detect and diagnose plant diseases. The proposed architecture can assist farmers in increasing both the quantity and quality of their agricultural productivity. Besides this, the OP-CNN helps to reduce disease prevalence through early detection. The performance of our proposed model is compared with other convolutional neural networks (CNN) architectures in order to validate its capability. The strawberry dataset was employed to train and test the models since the strawberry is one of the main crops in the Larache Province (Morocco). The experimental tests demonstrate that our proposed OP-CNN reaches the highest values versus DenseNet121, VGG19, and ResNet50 with 100%, 99%, 97%, and 63% respectively for classification accuracy, 100%, 100%, 98% and, 79% respectively for precision, 100%, 99%, 97%, and 63% respectively for recall, and 100%, 99%, 97%, and 58% respectively for "F" _1Score.

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1. INTRODUCTION

The agriculture domain serves as a significant sector in developing countries such as Morocco, and it contributes an important gross domestic product (GDP) percentage to their national revenue. Due to the weather conditions and the biotic factors, agricultural productivity is decreasing day by day. Climate change and other factors lead to diseases in the plant, which have an impact on livestock and human health. For that, plant diseases are a major source of concern, and they limit the increase in agricultural productivity. In Morocco, most farmers use traditional techniques to detect diseases in plant crops by inspecting the quality of their plants daily. This issue increases the number of labourers and decreases the crop productivity. Recently, artificial intelligence (AI) tools represent a good and appropriate solution to avoid the traditional techniques used in the agricultural sector by offering the intelligence proprieties such as learning, self-adapting, classification capability, and more [1]-[5]. These benefits enable us to create intelligent agricultural systems that will help farmers in improving their agricultural productivity, which is our study's goal. In this regard, many approaches and procedures for identifying and diagnosing plant diseases have been developed and tested by researchers. As per [6], the authors have proposed an intelligent diagnosis system for plant diseases named PD^{2}SE-Net to identify various plant diseases and estimate their severity. For training different plant images, they are used ResNet-50 architecture as the basic model. In Tiwari *et al.* [7], the authors proposed the dense convolutional neural networks (Dense-Net) to detect plant diseases and classification using leaf images. In Abas *et al.* [8], the authors have discussed the prospect of using VGG 16 architecture for plant classification. In Wang *et al.* [9], a trilinear convolutional neural networks model (T-CNN) was used to identify and detect the plant diseases. In Kumar *et al.* [10], the authors suggested the exponential spider monkey optimization (ESMO) for plant diseases identification. In Neelakantan [11], various machine learning algorithms were developed in order to find the best technique for classifying plant diseases. As consequence, plant diseases diagnosis is a very challenging topic in precision agriculture.

As seen from previous works cited above, the deep neural network architectures have been widely applied in the diagnosis and the detection of plant diseases with significant results. However, the use of other new convolutional neural networks (CNN) architecture is still required to reach high performance with fewer parameters. This paper proposes the convolutional neural networks architecture versus other algorithms founded in plant diseases detection and diagnosis due to their capabilities in identifying the diseases of plants and their ability to extract the features of the image, which achieves high accuracy in comparison with machine learning algorithms [12]. In this study, we built our model using CNN (OP-CNN) for strawberry plant diseases diagnosis. The strawberry plant is among the main crop of the Larache Province (northern Morocco). The performance of the proposed architecture is compared with the most commonly used CNN architectures in various works, such as DenseNet 121, VGG 19, and ResNet 50.

The rest of this paper is organized as follows: section 2 presents and describes our proposed OP-CNN architecture. Section 3 describes all methods used for plant diseases diagnosis. Section 4 provides the result and discussion of the performance between our proposed architecture and other CNN architectures. Finally, the conclusion of the work and perspectives were highlighted in section 5.

2. THE PROPOSED OP-CNN ARCHITECTURE

In this article, we aim to create our architecture (OP-CNN) to diagnose strawberry plant diseases for helping the farmers to make the right decisions. The proposed OP-CNN will be evaluated by comparing it to other CNN architectures in terms of the performance. At the beginning of the proposed OP-CNN training procedure as shown in Figure 1, we preprocessed our dataset, and then we applied the data augmentation technique to increase the number of plant images.

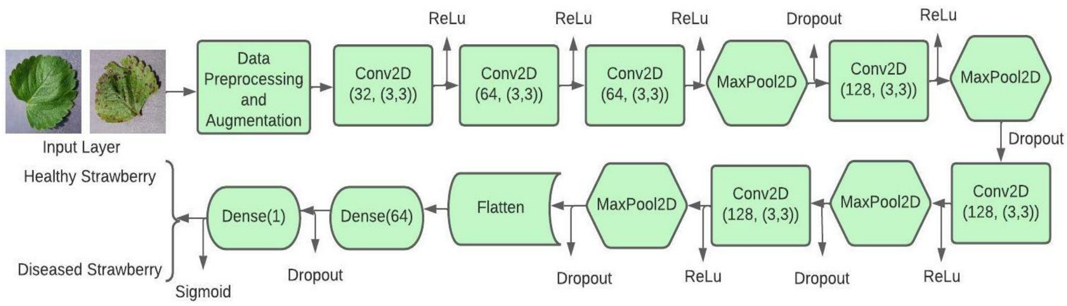

Figure 1. The proposed OP-CNN architecture

The proposed OP-CNN consists of six convolutional layers, four Maxpooling layers, and two fully connected layers. During the training phase, our OP-CNN receives a fixed-size (224×224) image as input, which is then passed through a convolutional layer, where we use the 32 filters with small size: (3×3). This convolution produces 32 features maps with dimensions of (222×222). The features maps obtained will be entered into a second convolutional layer with 64 filters that is (3×3) in size, and the features maps of the second convolutional layer will be transmitted to the third convolutional layer with 64 filters. Then, we included the max-pooling to reduce the image size, parameters, and calculation. Max-pooling is carried out over a (2×2) size. Following that, we added three convolutional layers, where we use 128 filters with size: (3×3). In addition, we add the max-pooling after each convolutional layer.

In order to complete our proposed architecture, we add two fully connected layers after a stack of convolutional layers series. The first Fully connected layer contained 64 neurons and the second is the sigmoid layer because we have the binary classification problem. The architecture of the proposed OP-CNN is shown in Figure 1. In our proposed architecture, we use the activation function (ReLu, i.e, rectified linear unit), dropout (for avoiding the overfitting problem), and sigmoid function for binary classification (In our case, we have two classes i.e., healthy and diseased strawberry) (see Figure 1).

3. RESEARCH METHOD

3.1. Data pre-processing

The OP-CNN model we propose, as well as other CNN architectures, is divided into two phases. The first is data pre-processing and augmentation. The second is plant disease detection and diagnosis using the proposed models. This study relies on data from the Kaggle since our Larache Province (northern Morocco) currently lacks strawberry-specific data. The strawberry dataset contained two classes (healthy strawberry and diseased strawberry that is affected by leaf scorch disease). The dataset used represents 2000 images in totality. For pre-processing step, we divided the dataset randomly into 80% for the training phase and 20% for the testing phase using the Spyder platform.

3.2. Data augmentation

Data augmentation (DA) is a technique used in deep learning to generate new images from the original dataset by random transformation. The goal of the DA technique is to solve the problem of few images in the training phase. According to this issue, the network can give unsatisfactory results. For that, the data augmentation adds the noise in the dataset to improve the generalizability of the model's results when confronted with new images. Furthermore, the data augmentation technique can overcome the overfitting issue [13], [14].

3.3. Convolutional neural networks CNN

Artificial intelligence (AI) has been widely applied in various areas, and it has emerged as a critical tool for the advancement of the world [15]. In the agriculture field, AI helps the farmers to use the intelligence systems and technologies thanks to their intelligence features compared to traditional techniques [16]-[18]. In this paper, we propose convolutional neural networks (CNN). The CNN is one of many Artificial Intelligence methods; more precisely is a type of the Neural Network employed in the computer vision domain [19], [20]. The main success of CNN is its ability to learn and classify large image datasets with great results [21] versus traditional neural networks and machine learning algorithms that increase the level of plant diseases detection [12].

3.4. CNN architectures

There are several architectures for CNN. For that purpose, the proposed OP-CNN model is compared in this study to the most commonly used architectures in plant disease diagnosis (or identification), such as DenseNet, VGGNet, and ResNet. These architectures are pre-trained and based on transfer learning.

- DenseNet is a dense convolutional neural network created and suggested by Tsinghua and Cornwell University and Facebook AI Research [22]. In a feed-forward manner, DenseNet connects each layer to the other layers. Among the advantage of DenseNet architecture is the improvement of feature propagation and minimizing the number of parameters. The DenseNet combines the input layer, convolutional layers (Conv) series, global average pooling, Fully Connected layers, and so on. For our research, we used DenseNet 121, which is a type of DenseNet.
- VGGNet is a visual geometry group net suggested by Simonyan and Zisserman [23] and was got second place in the 2014 competition. The VGGNet was trained previously on the ImageNet dataset. This architecture has a good power to extract the features image and consists of the Input layer, convolutional layers series, maxpooling, and fully connected layers. This paper proposes VGG 19, a VGGNet variant with 19 deep layers [24].
- ResNet is a residual neural network introduced in the 2015 competition and was a winner of this competition by giving significant results in classifying the ImageNet dataset with the minimum error. The ResNet model offers different benefits, such as reducing the difficulty of training deep neural networks and optimizing the parameters [25]. The ResNet structure contains the input layer, convolutional layers series (Conv), batch normalization (BN), global mean pooling (GMP), and Fully Connected layers. In our work, we propose ResNet 50 type with 50 deep layers.

4. RESULTS AND DISCUSSION

The proposed OP-CNN and other CNN architectures were trained using a strawberry plant dataset, as illustrated in Figure 2, where Figure 2(a) shows healthy strawberries and Figure 2(b) shows diseased strawberries (i.e., strawberries leaf scorch). The strawberry plant dataset was divided into train and test sets as shown in Table 1, and the performance of the OP-CNN and other CNN architectures was evaluated using the testing set. Thus, the different validation metrics used for examining the overall effectiveness and the quality of the prediction models (i.e., classification accuracy, precision, recall, F_1Score, and confusion matrix) are described in (1)-(4) and Figure 3.

(a) (b)

Figure 2. Images from our used strawberry plant dataset (a) healthy strawberry and (b) strawberry leaf scorch

Table 1. Original strawberry plant dataset division into train and test sets

Class/total	Training (80%)	Test (20%)	Total (100%)
Healthy strawberry	800	200	1,000
Diseased strawberry (leaf scorch)	800	200	1,000
Total	1,600	400	2,000

$$Classification\ accuracy = \frac{TP+TN}{Total\ number\ of\ plant\ images} \tag{1}$$

$$Precision\ \ (Pre) = \frac{TP}{TP+FP} \tag{2}$$

$$Recall\ (Rec) = \frac{TP}{TP+FN} \tag{3}$$

$$F_1Score\ (F_1) = 2 \times \frac{(Pre \times Rec)}{(Pre + Rec)} \tag{4}$$

Classification accuracy is the percentage of the sum of true positive and true negative on the total number of plant images, as expressed in (1). The precision metric indicates the number of correct predictions made by the model, as expressed in (2). The recall and F_1Score metrics represent the predictive model's effectiveness, as expressed in (3) and (4).

Before transferring the models to the training step, we used the data augmentation criteria (e.g., shear range, zoom range, horizontal flip, and so on) to increase the number of strawberry plant images and improve the accuracy performance of the models. Furthermore, all models have the same image size as input (224×224), optimization method (Adam), and same size of selected batch (32). The proposed OP-CNN and other CNN architectures were compiled with GPU support and realized with the Keras framework that represents an open-source library of deep neural networks using Python language.

4.1. The experimental tests

Figure 3 depicts the confusion matrix for all models used. According to Figure 3(a), the proposed OP-CNN produces more excellent performance than other state-of-the-art CNN architectures, indicating that the OP-CNN classified correctly all strawberry plant images with 0 misclassifications. Strawberry plants were nearly correctly classified using DenseNet 121 and VGG 19 with 2 and 10 respectively for misclassifications, as shown in Figure 3(b) and Figure 3(c). In comparison, ResNet 50 has 147 misclassifications, resulting in poor performance, as shown in Figure 3(d).

As seen in Table 2, the proposed architecture and other CNN architectures obtain nearly similar ratios of precision, recall, and F_1Score, except ResNet 50, which provide unsatisfying performance. Moreover, the proposed OP-CNN offer best performance for all classes during ten epochs versus 30 epochs for other CNN architectures. As a result, the proposed OP-CNN significant improves the performance outcomes with fewer epochs.

From Table 3, it can be noticed that the OP-CNN model gives the best average (100%) in all validation metrics versus CNN architectures. Furthermore, Figure 4 shows that the proposed OP-CNN architecture reaches the highest value against DenseNet 121, VGG 19, and ResNet 50 in classification with 100%, 99%, 97%, and 63%, respectively for accuracy. Figure 4 illustrates the classification accuracy achieved by the proposed OP-CNN and other CNN architectures in the test set.

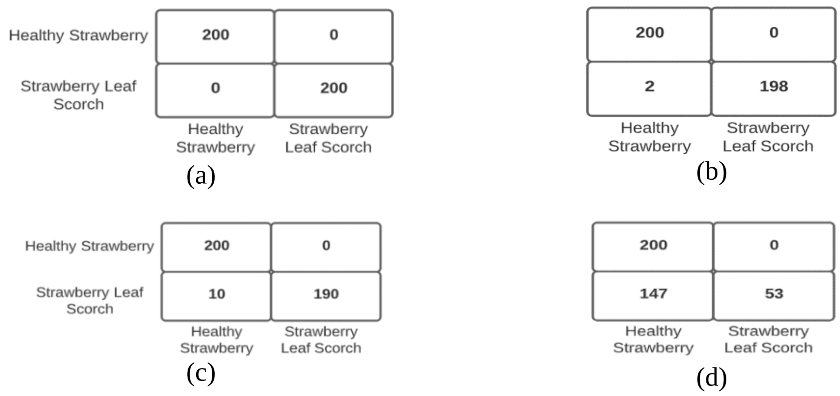

Figure 3. The confusion matrix comparison between (a) the proposed OP-CNN, (b) DenseNet 121, (c) VGG 19, and (d) ResNet 50 for each class (healthy strawberry and diseased strawberry (i.e., strawberry leaf scorch))

Table 2. The performance of the proposed OP-CNN vs. DenseNet 121, VGG 19, and ResNet 50 using a test set for each class

CNN architectures and OP-CNN	Classes	Precision (%)	Recall (%)	F_1 Score (%)	Epoch Numbers
DenseNet 121	Healthy Strawberry	99%	100%	100%	30
	Diseased Strawberry	100%	99%	99%	
VGG 19	Healthy Strawberry	95%	100%	98%	30
	Diseased Strawberry	100%	95%	97%	
ResNet 50	Healthy Strawberry	58%	100%	73%	30
	Diseased Strawberry	100%	27%	42%	
OP-CNN	Healthy Strawberry	100%	100%	100%	10
	Diseased Strawberry	100%	100%	100%	

Table 3. Average results of the proposed OP-CNN and CNN architectures on the test set

CNN architectures and OP-CNN	Average precision (%)	Average Recall (%)	Average F_1 Score (%)
DenseNet 121	100%	99%	99%
VGG 19	98%	97%	97%
ResNet 50	79%	63%	58%
OP-CNN	100%	100%	100%

From the results obtained, we can conclude that the proposed OP-CNN outperforms CNN architectures, in particular ResNet 50 (i.e., the classification accuracy of 100% for OP-CNN and 63% for ResNet 50). The best improvement of the proposed OP-CNN architecture in the classification accuracy was 1% than DenseNet 121, 3% than VGG 19, and 37% than ResNet 50 on average (see Figure 4). The ultimate objective of this study is to propose another efficient architecture to diagnose and detect the diseases of the strawberry plant, which is among the problem found in the Larache Province (northern Morocco). Additionally, the proposed OP-CNN was compared to other state-of-the-art CNN architectures in order to evaluate its performance.

The early detection of plant images represents a challenging task in agriculture precision. For that reason, our proposed model is highly accurate and appears to be promising for improving agricultural productivity through the early detection of strawberry plant diseases, which provide farmers to take adequate solutions. Therefore, the proposed OP-CNN can replace the traditional technique used for farmers with high-quality diagnosis and classification. Besides that, the proposed architecture could decrease the number of labourers and increase agricultural productivity.

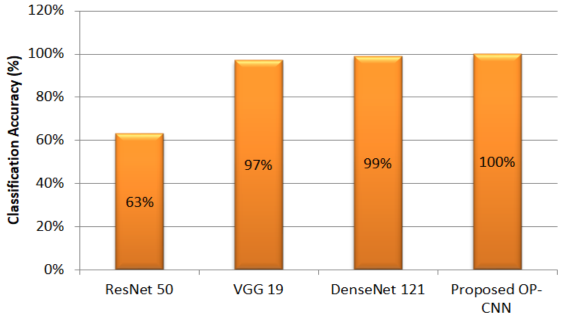

Figure 4. The classification accuracy comparison between the proposed OP-CNN and other CNN architectures on the test set

5. CONCLUSION

Plant disease diagnosis and identification is a very important task. In recent years, Morocco has experienced declining agricultural productivity in most of its regions due to climate change and other factors such as biotic factors. Strawberry is a major crop in the Larache Province (northern Morocco). Therefore, in this work, we proposed the OP-CNN architecture to diagnose and detect strawberry plant diseases to assist farmers in making the best decision. To validate the performance of the proposed architecture, we compared it to other CNN architectures in terms of classification accuracy, precision, recall, and F_1score. The experimental tests demonstrate that the proposed OP-CNN is capable to detect the plant diseases of the strawberries, and it significantly improves the diagnosis task. Thus, the main contributions of this article are given as follows: a) this work contributes by proposing another accurate OP-CNN architecture to diagnose and detect strawberry plant diseases; b) the proposed OP-CNN achieved an excellent performance compared to DenseNet 121 VGG 19, and ResNet 50 with 100%, 99%, 97%, and 63% respectively for classification accuracy; c) the proposed OP-CNN reached better average results versus DenseNet 121, VGG 19, and ResNet 50 with 100%, 100%, 98% and, 79% respectively for precision, 100%, 99%, 97%, and 63% respectively for recall, and 100%, 99%, 97%, and 58% respectively for F_1Score.

In the future article, we aim to use the real dataset from Larache Province (northern Morocco) for testing and validating various CNN architectures and the proposed architecture. Additionally, we will improve the ResNet 50 architecture in accuracy terms. These objectives help the farmers of this province to increase their crop productivity by limiting yield losses.

REFERENCES

[1] Sharma, M. Georgi, M. Tregubenko, A. Tselykh, and A. Tselykh, "Enabling smart agriculture by implementing artificial intelligence and embedded sensing," *Comput. Ind. Eng.*, vol. 165, no. January, p. 107936, 2022, doi: 10.1016/j.cie.2022.107936.
[2] Subeesh and C. R. Mehta, "Automation and digitization of agriculture using artificial intelligence and internet of things," *Artif. Intell. Agric.*, vol. 5, pp. 278–291, 2021, doi: 10.1016/j.aiia.2021.11.004.
[3] Gwagwa *et al.*, "Road map for research on responsible artificial intelligence for development (AI4D) in African countries: The case study of agriculture," *Patterns*, vol. 2, no. 12, p. 100381, 2021, doi: 10.1016/j.patter.2021.100381.
[4] J. Jung, M. Maeda, A. Chang, M. Bhandari, A. Ashapure, and J. Landivar-Bowles, "The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems," *Curr. Opin. Biotechnol.*, vol. 70, pp. 15–22, 2021, doi: 10.1016/j.copbio.2020.09.003.
[5] L. W. Liu, X. Ma, Y. M. Wang, C. T. Lu, and W. S. Lin, "Using artificial intelligence algorithms to predict rice (Oryza sativa L.) growth rate for precision agriculture," *Comput. Electron. Agric.*, vol. 187, 2021, doi: 10.1016/j.compag.20 21.106286.
[6] Q. Liang, S. Xiang, Y. Hu, G. Coppola, D. Zhang, and W. Sun, "PD2SE-Net: Computer-assisted plant disease diagnosis and severity estimation network," *Comput. Electron. Agric.*, vol. 157, pp. 518–529, 2019, doi: 10.1016/j.compag. 2019.01.034.
[7] V. Tiwari, R. C. Joshi, and M. K. Dutta, "Dense convolutional neural networks based multiclass plant disease detection and classification using leaf images," *Ecol. Inform.*, vol. 63, no. March, p. 101289, 2021, doi: 10.1016/j.ecoinf.2021.101289.
[8] M. A. H. Abas, N. Ismail, A. I. M. Yassin, and M. N. Taib, "VGG16 for plant image classification with transfer learning and data augmentation," *Int. J. Eng. Technol.*, vol. 7, no. 4, pp. 90–94, 2018, doi: 10.14419/ijet.v7i4.11.20781.
[9] D. Wang, J. Wang, W. Li, and P. Guan, "T-CNN: Trilinear convolutional neural networks model for visual detection of plant diseases," *Comput. Electron. Agric.*, vol. 190, no. July, p. 106468, 2021, doi: 10.1016/j.compag.2021.106468.
[10] S. Kumar, B. Sharma, V. K. Sharma, H. Sharma, and J. C. Bansal, "Plant leaf disease identification using exponential spider monkey optimization," *Sustain. Comput. Informatics Syst.*, vol. 28, p. 100283, 2020, doi: 10.1016/j.suscom.2018.10.004.
[11] P. Neelakantan, "Analyzing the best machine learning algorithm for plant disease classification," *Mater. Today Proc.*, 2021, doi: 10.1016/j.matpr.2021.07.358.
[12] R. Sujatha, J. M. Chatterjee, N. Z. Jhanjhi, and S. N. Brohi, "Performance of deep learning vs machine learning in plant leaf disease detection," *Microprocess. Microsyst.*, vol. 80, no. November 2020, p. 103615, 2021, doi: 10.1016/j.micpro.2020.103615.
[13] F. Chollet, "Deep learning with Python," *Manning Publications*, 2017.
[14] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: A simple way to prevent neural networks from overfitting," *J. Mach. Learn. Res.*, vol. 15, pp. 1929–1958, 2014.

[15] S. Belattar, O. Abdoun and E. Haimoudi, "A novel strategy for improving the counter propagation artificial neural networks in classification tasks," *J. Commun. Softw. Syst.*, vol. 18, no. 1, pp. 17–27, 2022, doi: 10.24138/jcomss-2021-0121.

[16] D. N. Varshitha and S. Choudhary, "An artificial intelligence solution for crop recommendation," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 25, no. 3, pp. 1688–1695, 2022, doi: 10.11591/ijeecs.v25.i3.pp1688-1695.

[17] G. Singh, A. Singh, and G. Kaur, "Role of artificial intelligence and the internet of things in agriculture," *Artif. Intell. to Solve Pervasive Internet Things Issues*, pp. 317–330, Jan. 2021, doi: 10.1016/B978-0-12-818576-6.00016-2.

[18] S. S. Yamaç, "Artificial intelligence methods reliably predict crop evapotranspiration with different combinations of meteorological data for sugar beet in a semiarid area," *Agric. Water Manag.*, vol. 254, no. 9, p. 106968, 2021, doi: 10.1016/j.agwat.2021.106968.

[19] A. Dixit and T. Kasbe, "Multi-feature based automatic facial expression recognition using deep convolutional neural network," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 25, no. 3, pp. 1406–1419, 2022, doi: 10.11591/ijeecs.v25.i3.pp1406-1419.

[20] D. I. Patrício and R. Rieder, "Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review," *Comput. Electron. Agric.*, vol. 153, no. April, pp. 69–81, 2018, doi: 10.1016/j.compag.2018.08.001.

[21] S. Rozlan and M. Hanafi, "Efficacy of chili plant diseases classification using deep learning : A Preliminary Study," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 15, no. 3, pp. 1–8, 2020, doi: 10.11591/ijeecs.v25.i3.pp1442-1449.

[22] G. Huang, Z. Liu, L. V. D. Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in *Proc. - 30th IEEE Conf. Comput. Vis. Pattern Recognition, CVPR 2017*, 2017, vol. 2017-Janua, pp. 2261–2269, doi: 10.1109/CVPR.2017.243.

[23] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in *3rd Int. Conf. Learn. Represent. ICLR 2015 - Conf. Track Proc.*, 2015, pp. 1–14.

[24] A. V. Ikechukwu, S. Murali, R. Deepu, and R. C. Shivamurthy, "ResNet-50 vs VGG-19 vs training from scratch: A comparative analysis of the segmentation and classification of Pneumonia from chest X-ray images," *Glob. Transitions Proc.*, vol. 2, no. 2, pp. 375–381, 2021, doi: 10.1016/j.gltp.2021.08.027.

[25] K. Zhang, B. Tang, L. Deng, and X. Liu, "A hybrid attention improved ResNet based fault diagnosis method of wind turbines gearbox," *Meas. J. Int. Meas. Confed.*, vol. 179, no. November 2020, p. 109491, 2021, doi: 10.1016/j.measurement.2021.109491.

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