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Smart agriculture model in detecting oil palm plantation diseases using a convolution neural network

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ABSTRACT

Planning models for sustainable crop care in the context of smart agriculture are complex issues as they involve many factors such as productivity, quality, growth sustainability, workforce use, and information technology use. In this study, we will create an optimized model using a convolution neural network (CNN) that can classify and monitor plant diseases. Part of the plant care system is to be aware of plant diseases and to be able to deal with them immediately. This study aims to acquire a new smart farming model for integrated crop care. The results of this research are findings in the form of a CNN model for classifying plant diseases detected from the leaves of the plants studied in oil palm. Testing using Google Colab obtains 100% accuracy and 99% accuracy using a teachable machine. The contributions of this paper create a new model in the field of informatics, especially in the field of intelligent agriculture based on information technology.

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1. INTRODUCTION

Smart agriculture [1]–[4] is one of the ways to realize artificial intelligence. The use of information technology in agriculture is part of smart agriculture. Smart agriculture is the concept of using agricultural devices that previously used manual methods and transitioning to automated devices using hardware and software modules that can be connected to the internet. Agriculture is important for meeting the nutritional needs of communities [5]. Especially in a country dominated by farmers [6].

The use of information technology in this field can increase efficiency and optimize crop yields by using artificial intelligence to predict the correct harvest [7]. So that the nutritional needs of human beings are properly met. Smart agriculture is inseparable from artificial intelligence or artificial intelligence. Agriculture no longer relies on soil conditions for nutrients and climate. With the use of information technology, the agricultural world has become more advanced, allowing farmers to thrive and meet their food needs. Thereby gradually solving problems in agriculture or farming, such as detection of pests and plant diseases [8].

There are several studies on smart agriculture, Olivia research [9] whose aim of this research is to implement a convolutional neural network (CNN) in the context of smart agriculture to detect disease in plants. CNN [10]–[13] is an artificial neural network architecture known for image processing and pattern recognition. In this study, the authors used a dataset of images of healthy plants and pictures of plants infected by various diseases. Using this dataset, they trained a CNN model to recognize visual patterns and features related to multiple plant diseases. After training the model, the authors used a discrete test dataset for accuracy. The results showed that CNN could identify conditions in plants with a high degree of accuracy. This can be used as a tool for farmers to quickly and accurately identify crop diseases.

Noshiri *et al.* [14] collected an image dataset of healthy plant leaves and leaves infected by various diseases in this study. They used CNN to train a model that can recognize and classify types of disease on plant leaves by using the visual information in the images. After training the model with the existing dataset, the authors tested its performance using a separate test dataset. Evaluation is carried out by measuring the accuracy of detecting and classifying diseases on plant leaves. The results showed that CNN could accurately detect and organize various types of infections on plant leaves with a high degree of accuracy. This research has important implications in smart agriculture, where early detection and recognition of plant diseases is critical to taking appropriate prevention and control measures. Using CNN, farmers can effectively identify foliar diseases in their crops and take necessary actions to minimize crop damage and increase productivity [15], [16].

Mo and Zhao [17] used an image dataset of healthy plant leaves and leaves infected by various diseases in this study. They trained CNN models using this dataset to recognize visual patterns and features related to plant disease. After preparing the model, the authors used a discrete test dataset for accuracy. Evaluation is done by measuring the accuracy of disease detection in plants. The results showed that CNN can accurately detect disease in plants with a high degree of accuracy.

Falaschetti *et al.* [18] collected an image dataset of different plant types and weeds. They use deep learning methods, specifically CNN, to train models that can recognize and classify weeds among crops using images' visual features. After preparing the model with the existing dataset, the authors tested its performance using a separate test dataset. Evaluation is done by measuring the accuracy of the detection and classification of weeds. The results showed that the use of deep learning, especially CNN, can accurately detect and classify various types of weeds with a high degree of accuracy. This research has important implications in precision agriculture, where correctly identifying and controlling weeds is essential to increase crop productivity.

Liu *et al.* [19] used an image dataset of healthy plants and plants infected by various diseases. They apply deep learning techniques, specifically CNN, to train models that can recognize and detect disease in plants using the visual features contained in images. After preparing the model using the existing dataset, the authors test its performance using a separate test dataset. Evaluation is done by measuring the accuracy of disease detection in plants. The results showed that using the deep learning technique, the model can detect disease in plants automatically with a high degree of accuracy. This research has important implications in agriculture, where early detection of plant diseases is essential for effective crop control and protection [20].

Rajeshkumar *et al.* [21] collected an image dataset of healthy tomato leaves and leaves infected by various diseases. They used CNN to train a model that can recognize and detect disease in tomato plants by using the visual features contained in the images. After preparing the model using the existing dataset, the authors tested its performance using a separate test dataset. The evaluation was carried out by measuring the accuracy of disease detection in tomato plants. The results showed that using deep learning, especially CNN, can effectively detect and classify various types of diseases in tomato plants with high accuracy. This research has important implications in agriculture, especially in detecting and controlling diseases in tomato plants.

Sarkar *et al.* [22] proposes an intelligent irrigation system utilizing CNN and IoT technologies. This system aims to optimize water use and improve irrigation efficiency in agriculture. The study results show that by using CNN and internet of things (IoT) technologies, smart irrigation systems can optimize water use by considering different plant conditions. This helps farmers reduce water wastage and increase irrigation efficiency, reducing operational costs and environmental impacts of excessive water use.

Frikha *et al.* [23]. collected an image dataset of healthy plants and plants infected by various pests and diseases. They apply deep learning methods, specifically CNN, to train models that can recognize and identify problems and disorders in plants using the visual features contained in images. The results showed that by using deep learning techniques, the model could identify and classify various types of pests and diseases in plants with a high degree of accuracy. This research has important implications in agriculture, particularly in the early detection and control of plant pests and diseases.

Beri and Rao [24] proposes an intelligent plant disease detection system utilizing deep learning and IoT technologies. This system is designed to monitor and detect plant diseases in real-time. The study results show that by using deep learning and IoT techniques, this system can accurately detect plant diseases and provide fast information to farmers. This allows farmers to take necessary precautions, such as applying appropriate curative treatments or pest control.

Boursianis *et al.* [25] proposes a smart farming system that utilizes deep learning and IoT technologies. This system is designed to monitor, analyze and manage various aspects of agriculture efficiently and automatically. Based on the analysis results, this system provides information and recommendations to farmers to manage their crops efficiently. For example, the system can guide timely irrigation, pest and disease control, optimal fertilization, and other agricultural actions. This research shows that by using deep learning and IoT techniques, smart farming systems can significantly increase agricultural productivity, efficiency, and sustainability.

This research is a follow-up to the research conducted by Kamilaris *et al.* [26], which resulted in a framework for smart agriculture through the implementation of the IoT. This IoT framework is used to collect, process and analyze data streams in real-time and facilitate the deployment of intelligent decision support solutions. Existing IoT-based solutions are largely domain-dependent, offering domain-focused process processing and analytics. In the context of the agri-food industry, different external parameters belong to different domains, such as weather conditions, regulations and others. Smart farming systems are still in development and will have a significant impact on the food supply chain, and a flexible and adaptable IoT framework is important to truly realize the concept of smart farming. This research aims to develop a semantic framework that can support smart agricultural applications based on the IoT. IoT is a physical network device connected and can interact with each other via the internet [27], [26].

In agriculture, IoT can collect data from various farm sensors and apply intelligent analysis to optimize crop production [28], [29]. This research proposes a semantic framework that includes four main layers: sensor and actuator layer, the monitoring layer, the knowledge processing layer, and the application layer. The sensor and actuator layer involves hardware such as temperature, humidity, light sensors, and actuators used to control irrigation or watering systems. The monitoring layer collects data from sensors and passes it on to the next layer. The knowledge processing layer uses semantic techniques to process the collected data and produce useful knowledge. Semantic techniques are used to analyze data, recognize patterns, and generate information that can be used for decision-making in war. The application layer implements agriculture-focused IoT-based applications, such as automated irrigation control or crop growth monitoring systems. In this study, the authors also identify several challenges that need to be overcome in implementing Agri-IoT, such as hardware and software interoperability, data security, and managing large data volumes. Creating the proposed semantic work can solve this challenge by enabling better integration between hardware and software, as well as more intelligent and efficient data analysis. This research makes an important contribution to developing IoT-based smart agricultural applications using a semantic approach. Building on the proposed semantic work can assist farmers in making better decisions, increasing production efficiency, and optimizing the use of agricultural resources. In this study, there is no model to classify plant diseases based on leaves to increase production efficiency and optimize the use of agricultural resources.

Unpredictable climate change is having a major impact on traditional agriculture. Extreme seasonal changes lead to crop failure and crop damage. This drastic climate change has also led to changes in agricultural development planning. In addition to pests and plant diseases, the effects of temperature, precipitation and natural disasters are the main causes of crop failure. Another factor contributing to climate change are greenhouse gases, which are responsible for the leakage of the ozone layer, so they affect the global climate [30].

The global agricultural sector is heavily influenced by a number of factors, including population growth, changing consumer lifestyles and changing market conditions. Achieving strong food security requires solutions that employ smart farming models to combat climate change while coping with changes in other interacting factors. Therefore, strategic action at the regional and international levels by governments, the private sector, academia and policymakers is required [31].

This management style, which involves monitoring, planning and controlling agricultural processes, is called smart farming. This leadership style involves many specialists or specialists, especially in the field of agriculture. By using software and hardware specifically designed to increase agricultural yields. Many vendors [32] are needed to develop the software and hardware for smart agriculture. Agriculture and smart farming businesses require ICT resources to deliver results efficiently, efficiently and profitably. This smart farming technology cannot be done alone, it requires collaboration with numerous agricultural and information technology experts. The decision-making model is combined with the agricultural work process model to form an intelligent agricultural model [33].

Smart Agriculture, developed by Wolfert *et al.* [34] is a development that emphasizes the use of ICT in the cyber-physical agricultural management cycle. The development of information technology, especially the IoT and cloud computing, has made great contributions to smart agriculture. The use of big data technology, data mining and artificial intelligence is applied to a large amount of data with different variations that can be collected, analyzed and used for decision making. In this established model, the latest findings in the application of information technology in smart agriculture will be obtained. Based on the problems above, researchers want to develop a smart farming model by adding a classification of plant diseases detected from plant leaves. The plants studied were oil palm and the technique used in this research is deep learning.

2. MATERIAL AND METHOD

2.1. Accuracy of convolutional neural network

This study focuses on modelling smart agriculture for crop protection. This study developed a plant classification model based on image processing of healthy and diseased plant leaves on oil palm. It is designed to quickly and accurately detect diseased palm for intelligent plant care. In this study, deep learning methods were used with the CNN algorithm to classify healthy and unhealthy plants by processing the image of leaves of oil palm. In this study, the programming language used is the Python programming language. It is used with other tools that import Python. All modules are declared using an image and saved to a dataset. Tests in this study use the Google Colab and teachable machine applications. The mathematical model for this study:

$$s(t) = (xt)(t) = (\alpha).w(t) = \infty \tag{1}$$

On (1), several symbols and variables need to be explained with $s(t)$ is function s with parameter t, representing a value or result at time t, xt is represents the variable x at time t, which may represent other relevant data or variables in the context of this formula, (t) is shows the exponent t of the variable xt, meaning that the variable xt is raised to the power of t, (α) is the constant α used in the formula. These constants' value and specific meaning will depend on the context or issue being discussed. Note that α is used in multiplication in this formula, $w(t)$ is a function w with parameter t, which may be a function associated with the variable xt or some other variable. These functions can also have different meanings and contexts depending on the context of the entire formula, and ∞ is the negative symbol for infinity. In this context, it shows that the result of this equation is negative infinity or is undefined.

The first argument is the input which is x and the second argument is w as the kernel or filter. If we look at the input as a two-dimensional image, we can say that t is a pixel and replace it with i and j. Therefore, the operation for convolution to input with more than one dimension can be written as (2):

$$s(i,j) = (K.I)(i,j) = (i+,j+)K(m,n) \tag{2}$$

This formula is used to describe the convolution operation on the convolution layer. Explanation of each symbol and variable in this formula with $s(i,j)$ is the output or activation at the pixel location (i,j) in the convolution layer, K is represents the kernel or convolution filter used in the convolution operation. This kernel function takes features from the input and produces output at each pixel location, I is the input to the convolution layer, (i,j) is indicates the position or location of the pixels in the input or output convolution layer, $(i+,j+)$ is represents shift or translation values in pixel coordinates. It is often used in convolution operations to set up the mapping between the input and output layers of the convolution, and $K(m,n)$ is a kernel or convolution filter with size m x n. The size of this kernel can vary depending on the CNN architecture used.

This formula describes how the convolution operation is performed on the convolution layer in the CNN. Each output at pixel location (i,j) is calculated by multiplying the K kernel and the corresponding area around that pixel in input I and then summing the results. This mapping can be controlled by shifting i+ and j+. The convolution operation on CNN enables feature extraction from the input image or data and helps in pattern recognition. This formula helps explain how convolution works in the CNN convolution layer to produce output channeled to the next layer in the network.

2.2. General architecture

General architecture is one of the most important parts in the detailed research process. In this research, of course, we detect disease from oil palm plantations where the data is based on image data which will be trained and tested with CNN in order to create smart agriculture in the future. The general architecture in this research is based on Figure 1. In Figure 1 is explained based on the following steps:

- The dataset was taken based on images of oil palm plantations based on healthy palm fronds and diseased palm leaves.
- Carry out data processing, extract data and group image data.
- After grouping the data by dividing it into training data and test data where the training data is measured using the slovin approach based on (3).

$$n = \frac{N}{1+Ne^2} \tag{3}$$

with n is the number of datasets to search, N is dataset size, and e is the margin of error value of the dataset size.

- Detection with CNN on training data
a. Input *neuron*
b. Performing a convolution layer by combining two series of numbers to produce a third number series
c. Measuring activation function with ReLu $f(x) = \max(x, 0)$.
- Detection with CNN on testing data
a. Input *neuron*
b. Performing a convolution layer by combining two series of numbers to produce a third number series
c. Measuring activation function with ReLu $f(x) = \max(x, 0)$.
- Measurement accuracy

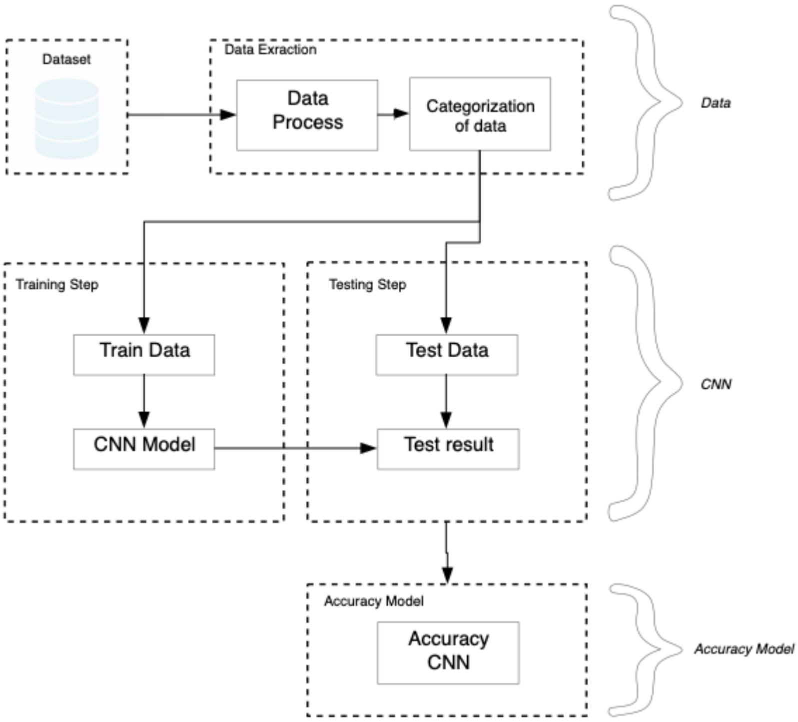

Figure 1. General architecture

3. RESULT AND DICUSSION

The novelty of this research is smart agricultural modeling using CNN to detect plant diseases in oil palm. Input on CNN is an image. The input image in CNN is represented in matrix form. Each pixel in the image is assigned an intensity value that represents the brightness or color of that pixel. Each element in this matrix or tensor represents an image pixel at a particular position. For example, if the image is grayscale, then the input matrix or tensor will have 2D dimensions, where each element represents a pixel intensity. If the image is color, the input matrix or tensor will have 3D dimensions, with each component representing intensity in a different color channel, e.g., red, green, or blue. CNN uses convolution filters or kernels to apply convolution operations to the input image. This filter moves across the image and takes a convolution mapping between the filter and a small area of the image. This convolution operation results in an output matrix or tensor that represents the features extracted from the input image. Image input in CNN is done in batches, which means several images are processed simultaneously. The input will have a higher dimension in the tensor, where the first dimension represents the number of images in the batch. CNN performs a training or inference process to recognize visual patterns and perform object classification, object detection, segmentation, or other tasks related to image processing. The following is an example of a sample data image in Figure 2, a sample data image of healthy palm leaves in Figure 3. In Figure 2 you can see several samples of the healthy palm fronds image. Where the data in the form of images is trained on a CNN in order to achieve accuracy in detection. The diseased palm leaves images can be seen in Figure 3.

In this section, it is explained how to get the results of the research that has been carried out starting from collecting datasets in the form of training data, data validation, and data testing. Then make the model and translate the model into the Python programming language version 3.10.2. The application used to test the dataset is the google colab application and teachable machine. Google Colab is a tool for running Python programs online on the web. The results of the model compilation using Google Colab for oil palm plants are shown in Table 1 and graphs of accuracy and loss as follows in Figures 3 and 4.

Figure 2. Sample of healthy palm fronds image

Figure 3. Sample of diseased palm leaves images

Table 1. Test results on palm plants

Iteration	Time/Step	Reduction	Accuracy	Reduction of Validation	Accuracy of Validation
1/30	13s 5s	0.2239	0.8889	24.3459	0.6667
5/30	2s 825ms	0.7419	0.6667	0.6176	0.7667
10/30	2s 671ms	0.7063	0.8889	0.8306	0.7000
15/30	2s 873ms	0.6296	0.7778	0.4768	0.9333
20/30	2s 816ms	0.8378	0.7778	0.6659	0.4333
25/30	2s 827ms	0.4964	0.8889	0.1628	1.0000
30/30	2s 894ms	0.2568	0.7778	1.4966	0.7000

From the research results shown in Table 1, the trial for oil palm plants obtained 100% accuracy, whereas from the 25 image datasets tested, all obtained correct results. This is evident from the graphs of the train and loss results shown in Figures 4 and 5. From the graphs in Figure 4, the accuracy is unstable but can achieve 100% accuracy in the 30th epoch or iteration. The compiled model produces 100% accuracy in the 30th epoch. Likewise, the model results obtained with teachable machine make 99% accuracy, so that this research can contribute to the field of smart agriculture for plant maintenance systems.

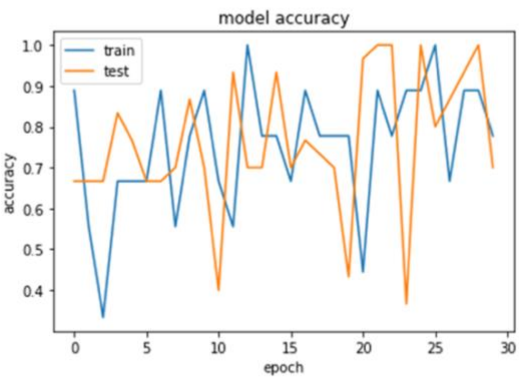

Figure 4. Model accuracy graph for palm leaves

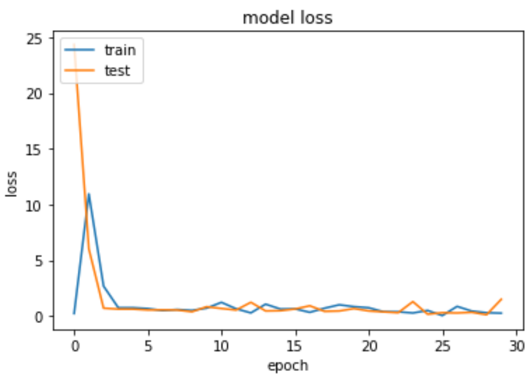

Figure 5. Loss model accuracy graph for palm leaves

4. CONCLUSIONS

In summary, the model compilation process shows that the time/step is still slow with 2 seconds 554 ms/step at the start of the iteration at the first epoch and 1 second 492 ms/step at the 30th epoch. The model compilation results show 100% accuracy at the 30th iteration, and the image data testing results show the same results. The research results show that the proposed method can achieve excellent accuracy in detecting oil palm diseases. From the graph of accuracy and loss, the model studied still shows unstable accuracy and loss which is caused by the lack of data used. This research also has important implications in the field of agriculture and planting, because it can help farmers and agronomists see the initial condition of oil palm and take the necessary actions to prevent the spread of this disease more widely.

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REFERENCES

[1] R. B. Wakweya, "Challenges and prospects of adopting climate-smart agricultural practices and technologies: implications for food security," *Journal of Agriculture and Food Research*, vol. 14, 2023, doi: 10.1016/j.jafr.2023.100698.
[2] B. Tadesse and M. Ahmed, "Impact of adoption of climate smart agricultural practices to minimize production risk in Ethiopia: A systematic review," *Journal of Agriculture and Food Research*, vol. 13, 2023, doi: 10.1016/j.jafr.2023.100655.
[3] G. Gebresenbet *et al.*, "A concept for application of integrated digital technologies to enhance future smart agricultural systems," *Smart Agricultural Technology*, vol. 5, 2023, doi: 10.1016/j.atech.2023.100255.
[4] E. O. Jones *et al.*, "Mobile agricultural extension delivery and climate-smart agricultural practices in a time of a pandemic: evidence from southern ghana," *Environmental and Sustainability Indicators*, vol. 19, 2023, doi: 10.1016/j.indic.2023.100274.
[5] A. R. L. Al-Khowarizmi, M. Lubis, and R. F. Rahmat, "Information technology based smart farming model development in agriculture land," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 11, no. 2, pp. 564-571, doi: 10.11591/ijai.v11.i2.pp564-571.
[6] G. Sushanth and S. Sujatha, "IOT based smart agriculture system," *2018 International Conference on Wireless Communications, Signal Processing and Networking, WiSPNET 2018*, vol. 5, no. 6, pp. 838–842, 2018, doi: 10.1109/WiSPNET.2018.8538702.
[7] T. Iizumi *et al.*, "Prediction of seasonal climate-induced variations in global food production," *Nature Climate Change*, vol. 3, no. 10, pp. 904–908, 2013, doi: 10.1038/nclimate1945.
[8] S. Cui, P. Ling, H. Zhu, and H. M. Keener, "Plant pest detection using an artificial nose system: a review," *Sensors*, vol. 18, no. 2, 2018, doi: 10.3390/s18020378.
[9] O. Debnath and H. N. Saha, "An IoT-based intelligent farming using CNN for early disease detection in rice paddy," *Microprocessors and Microsystems*, vol. 94, 2022, doi: 10.1016/j.micpro.2022.104631.
[10] X. Zhang, X. Zhou, M. Lin, and J. Sun, "ShuffleNet: an extremely efficient convolutional neural network for mobile devices," in *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2018, pp. 6848–6856, doi: 10.1109/CVPR.2018.00716.
[11] L. C. Chen, Y. Zhu, G. Papandreou, F. Schroff, and H. Adam, "Encoder-decoder with atrous separable convolution for semantic image segmentation," in *Computer Vision – ECCV 2018*, 2018, vol. 11211, pp. 833–851, doi: 10.1007/978-3-030-01234-2_49.
[12] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, "MobileNetV2: inverted residuals and linear bottlenecks," in *The IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2018, pp. 4510–4520, doi: 10.1109/CVPR.2018.00474.
[13] M. Tan and Q. V. Le, "EfficientNet: rethinking model scaling for convolutional neural networks," in *36th International Conference on Machine Learning, ICML*, 2019, vol. 2019, pp. 10691–10700.
[14] N. Noshiri, M. A. Beck, C. P. Bidinosti, and C. J. Henry, "A comprehensive review of 3D convolutional neural network-based classification techniques of diseased and defective crops using non-UAV-based hyperspectral images," *Smart Agricultural Technology*, vol. 5, 2023, doi: 10.1016/j.atech.2023.100316.
[15] N. K. Trivedi *et al.*, "Early detection and classification of tomato leaf disease using high-performance deep neural network," *Sensors*, vol. 21, no. 23, 2021, doi: 10.3390/s21237987.
[16] G. Latif, S. E. Abdelhamid, R. E. Mallouhy, J. Alghazo, and Z. A. Kazimi, "Deep learning utilization in agriculture: detection of rice plant diseases using an improved CNN model," *Plants*, vol. 11, no. 17, 2022.
[17] H. Mo and G. Zhao, "RIC-CNN: rotation-invariant coordinate convolutional neural network," *Pattern Recognition*, vol. 146, 2024, doi: 10.1016/j.patcog.2023.109994.
[18] L. Falaschetti, L. Manoni, D. D. Leo, D. Pau, V. Tomaselli, and C. Turchetti, "A CNN-based image detector for plant leaf diseases classification," *HardwareX*, vol. 12, 2022, doi: 10.1016/j.ohx.2022.e00363.
[19] Y. Lu, X. Wu, P. Liu, H. Li, and W. Liu, "Rice disease identification method based on improved CNN-BiGRU," *Artificial Intelligence in Agriculture*, vol. 9, pp. 100–109, 2023, doi: 10.1016/j.aiia.2023.08.005.
[20] Y. Li, J. Nie, and X. Chao, "Do we really need deep CNN for plant diseases identification?," *Computers and Electronics in Agriculture*, vol. 178, 2020, doi: 10.1016/j.compag.2020.105803.
[21] G. Rajeshkumar *et al.*, "Smart office automation via faster R-CNN based face recognition and internet of things," *Measurement: Sensors*, vol. 27, 2023, doi: 10.1016/j.measen.2023.100719.
[22] S. Sarkar *et al.*, "Cyber-agricultural systems for crop breeding and sustainable production," *Trends in Plant Science*, vol. 29, no. 2, pp. 130–149, 2024, doi: 10.1016/j.tplants.2023.08.001.
[23] T. Frikha, J. Ktari, B. Zalila, O. Ghorbel, and N. B. Amor, "Integrating blockchain and deep learning for intelligent greenhouse control and traceability," *Alexandria Engineering Journal*, vol. 79, pp. 259–273, 2023, doi: 10.1016/j.aej.2023.08.027.
[24] D. C. Beri and B. V. A. N. S. S. P. Rao, "Intelligent plant disease detection system," in *AIP Conference Proceedings*, 2023, vol. 2788, no. 1, doi: 10.1063/5.0150097.
[25] A. D. Boursianis *et al.*, "Internet of things (IoT) and agricultural unmanned aerial vehicles (UAVs) in smart farming: a comprehensive review," *Internet of Things*, vol. 18, 2022, doi: 10.1016/j.iot.2020.100187.
[26] A. Kamilaris, F. Gao, F. X. P. -Boldu, and M. I. Ali, "Agri-IoT: A semantic framework for Internet of Things-enabled smart farming applications," in *2016 IEEE 3rd World Forum on Internet of Things, WF-IoT 2016*, 2016, pp. 442–447, doi: 10.1109/WF-IoT.2016.7845467.

[27] B. B. Sinha and R. Dhanalakshmi, "Recent advancements and challenges of internet of things in smart agriculture: a survey," *Future Generation Computer Systems*, vol. 126, pp. 169–184, 2022.

[28] J. Muangprathub, N. Boonnam, S. Kajornkasirat, N. Lekbangpong, A. Wanichsombat, and P. Nillaor, "IoT and agriculture data analysis for smart farm," *Computers and electronics in agriculture*, vol. 156, pp. 467–474, 2019.

[29] E. S. Mohamed, A. A. Belal, S. K. Abd-Elmabod, M. A. El-Shirbeny, A. Gad, and M. B. Zahran, "Smart farming for improving agricultural management," *The Egyptian Journal of Remote Sensing and Space Science*, vol. 24, no. 3, pp. 971–981, 2021.

[30] Beecham, "Towards smart farming: agriculture embracing the IoT vision," *Beechham Research Report*, vol. 44, 2014.

[31] I. Arakelyan, D. Moran, and A. Wreford, "Climate smart agriculture: a critical review," in *Making Climate Compatible Development Happen*, pp. 66–86, 2017, Routledge, doi: 10.4324/9781315621579.

[32] J. W. Kruize, J. Wolfert, H. Scholten, C. N. Verdouw, A. Kassahun, and A. J. M. Beulens, "A reference architecture for farm software ecosystems," *Computers and Electronics in Agriculture*, vol. 125, pp. 12–28, 2016, doi: 10.1016/j.compag.2016.04.011.

[33] M. J. O'Grady and G. M. P. O'Hare, "Modelling the smart farm," *Information Processing in Agriculture*, vol. 4, no. 3, pp. 179–187, 2017, doi: 10.1016/j.inpa.2017.05.001.

[34] S. Wolfert, L. Ge, C. Verdouw, and M. J. Bogaardt, "Big data in smart manufacturing," *Agricultural systems*, vol. 153, pp. 69–80, 2017, doi: 10.1016/j.agsy.2017.01.023.

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