

# Comparative Analysis Of CNN Models For Lettuce Leaf Disease Detection In Hydroponic Farming

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## ABSTRACT:

Hydroponic farming is rapidly growing in the Philippines as a sustainable solution for small-scale farmers especially in regions like Nueva Ecija. Although hydroponically grown lettuce has several advantages, it is highly susceptible to diseases that affects quality and productivity. Thus, prompt and accurate detection of disease is essential in reducing losses and ensuring sustainable production. This study presents a comparative analysis of three commonly use Convolutional Neural Network (CNN) models, namely EfficientNet, InceptionV3, and ResNet50 to identify the best CNN model which detect lettuce leaf diseases in hydroponic systems. A diverse dataset collected from online sources and local hydroponic farms in Nueva Ecija, subsequently augmented, generating a total of 1,056 images. Transfer learning was used to train each CNN model and evaluated across three test scenarios including the distinction of lettuce from non-lettuce, classification of diseased versus non-lettuce, and identification of specific disease utilizing classification accuracy. The results show that EfficientNet achieved the highest overall mean accuracy of 92.31%, outperforming the other models in every test scenarios. On the other hand, InceptionV3 and ResNet50 revealed difficulties in classifying non-disease and healthy leaves. These findings indicate that EfficientNet could be an instrumental component for developing automated diagnostic applications to monitor diseases on hydroponic farms. The study recommends the dataset should be expanded, and that agricultural stakeholders should collaborate to develop CNN-based detection applications that are more practical and useful in real-life settings. This would help hydroponic farming in the Philippines become more sustainable and profitable.

**KEYWORDS:** Hydroponic Farming, Lettuce Leaf Disease, Lettuce Leaf Disease Detection, Machine Learning, Deep Learning, Convolutional Neural Network

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## 1) INTRODUCTION:

With the world's population increasing each year and environmental concerns like climate change and depleting natural resources, there is an increasing demand for efficient and sustainable agricultural practices for supplementing food production [1] [14]. Land degradation, water scarcity, and increasing expenses are making traditional soil-based agriculture less efficient [7] [18] [19]. In response, hydroponic farming has emerged as a promising alternative, offering a soilless method of cultivation in a controlled environment [13]. This method enhances resource efficiency, significantly reducing water usage by up to 90% through recirculating systems and mitigating the risk of soil-borne pests and diseases [10]. These advantages make hydroponics an ideal solution for improving food security, especially in urban and peri-urban settings.

In spite of its advantages, hydroponic farming has limitations, particularly when it comes to high-value crops like lettuce (*Lactuca sativa*). Crop resistance to diseases is still a major concern because, if not controlled, a single outbreak can result in large yield and financial losses [3] [8]. Traditionally, diseases are identified by experts by examining the leaves of plants. However, small-scale farmers find this approach to be time-consuming, subjective, and inaccessible in resource-constrained places like Nueva Ecija, Philippines [2]. A fast, reliable, and readily available diagnostic tool is crucial for farming operations to be profitable.

Recent developments in artificial intelligence (AI) present an effective means to address this diagnostic challenge. In terms of automatically recognizing crop diseases from leaf images, Convolutional Neural Networks (CNNs), a subset of deep learning, showed exceptional performance [6] [9]. CNN models can analyze visual characteristics like spots, lesions, and discoloration to recognize diseases with an accuracy which is commonly comparable to trained professionals [4]. Transfer learning, which reduced training

time and computational needs by allowing pre-trained models like InceptionV3, ResNet50, and EfficientNet to be customized for agricultural use [20] [17], has further improved the efficiency of this approach. According to studies, CNNs are currently able to detect hydroponic lettuce diseases with accuracy [12].

Despite the significant advancements, these technologies are still not commonly utilized in certain settings. Most of the existing research and mobile disease diagnosis applications focus on crops produced in traditional soil-based environments and rely on generalized datasets. In the Philippines, there aren't many local, specialized devices designed to meet the specific demands of hydroponic farms, especially for small-scale farmers. This gap presents an important challenge to the region's complete adoption of sustainable hydroponic systems.

To address this challenge, this research aims to compare the effectiveness of different CNN models to recognize lettuce leaf diseases that are particularly designed for hydroponic farms in Nueva Ecija. Identifying the most beneficial and effective deep learning model for early disease detection is the goal. By identifying the most suitable deep learning model for this specific case, the study will contribute to the region's hydroponic farming sustainability by encouraging consistent, high-quality yields and advancing more general food security goals.

This section discusses how three popular CNN models for image classification were compared. The method is divided into four primary components: (1) Preparation of Dataset, (2) CNN Models, (3) Implementation of CNN Models, and (4) Evaluation of CNN models.

### **2.1 Preparation of Dataset**

A dataset of images of lettuce leaves was collected from online sources and hydroponic farms in Nueva Ecija, Philippines, to gather a range of disease conditions. The images were separated into five classes, namely Tip Burn, Alternaria Leaf Spot, Powdery Mildew, Downy Mildew, and Healthy. To create supplementary images for each class, data augmentation techniques such as flipping horizontally, and rotating images were used. Consequently, 1056 pictures were generated. The datasets were separated into three categories: testing, validation, and training.

### **2.2 CNN Models**

This study used three CNN models that are often employed for image processing including EfficientNet, InceptionV3, and ResNet50. These CNN models are trained on pre-processed data in order to accurately identify lettuce leaf disease in hydroponics. The ability of these CNN models to accurately identify is then evaluated which will provide information about how well the CNN models in detecting lettuce leaf disease.

### **2.3 Implementation of CNN Models**

All CNN models were implemented and trained using Python, applying the TensorFlow deep learning framework. Transfer learning was employed by integrating pre-trained weights for each model followed by retraining the last layers of the models on the lettuce leaf dataset. This approach improves learning efficiency and accuracy, especially when there is limited dataset.

### **2.4 Evaluation of CNN Models**

The performance of each CNN model was mainly evaluated using classification accuracy across three test scenarios, each representing different classification challenges including the distinction between lettuce and non-lettuce images, classification between diseased, and non-lettuce, and identification of a specific lettuce leaf disease and healthy lettuce.

## **3) RESULTS:**

This section compared three CNN models in order to identify the most effective for hydroponic lettuce leaf disease detection. The comparison emphasized on the efficiency with which each CNN model detected different lettuce leaf conditions. The intention of this evaluation was to determine which CNN model could most effectively facilitate early and accurate disease detection in actual hydroponic farming environments.

### **.1. CNN Models**

#### **3.1.1. EfficientNet**

EfficientNet is a group of CNN model. It introduced compound scaling, a new way to scale that balances network width, depth, and resolution in a systematic way to get high accuracy with fewer computations and parameters [17]. It scales all dimensions at once, compared to previous models that only scaled one or two dimensions at a time.

### 3.1.2. InceptionV3

InceptionV3 architecture is a deep CNN that is based on the Inception (GoogLeNet) family. It adds parallel convolutional paths with kernels of different sizes to get features from each layer at different scales [15]. Using factorized convolutions, auxiliary classifiers, and batch normalization makes it better at generalizing and costs less to run..

### 1.3. ResNet50

ResNet50 is a part of the ResNet (Residual Network) family. It is different from other networks in that it uses bypass (shortcut) connections for residual learning. This alleviates the issue of gradients vanishing and enables it to train very deep networks [5]. Each of the remaining block makes optimization easier and ends loss as networks go deeper by letting information through particular levels.

### 3.2. Comparison of CNN Models

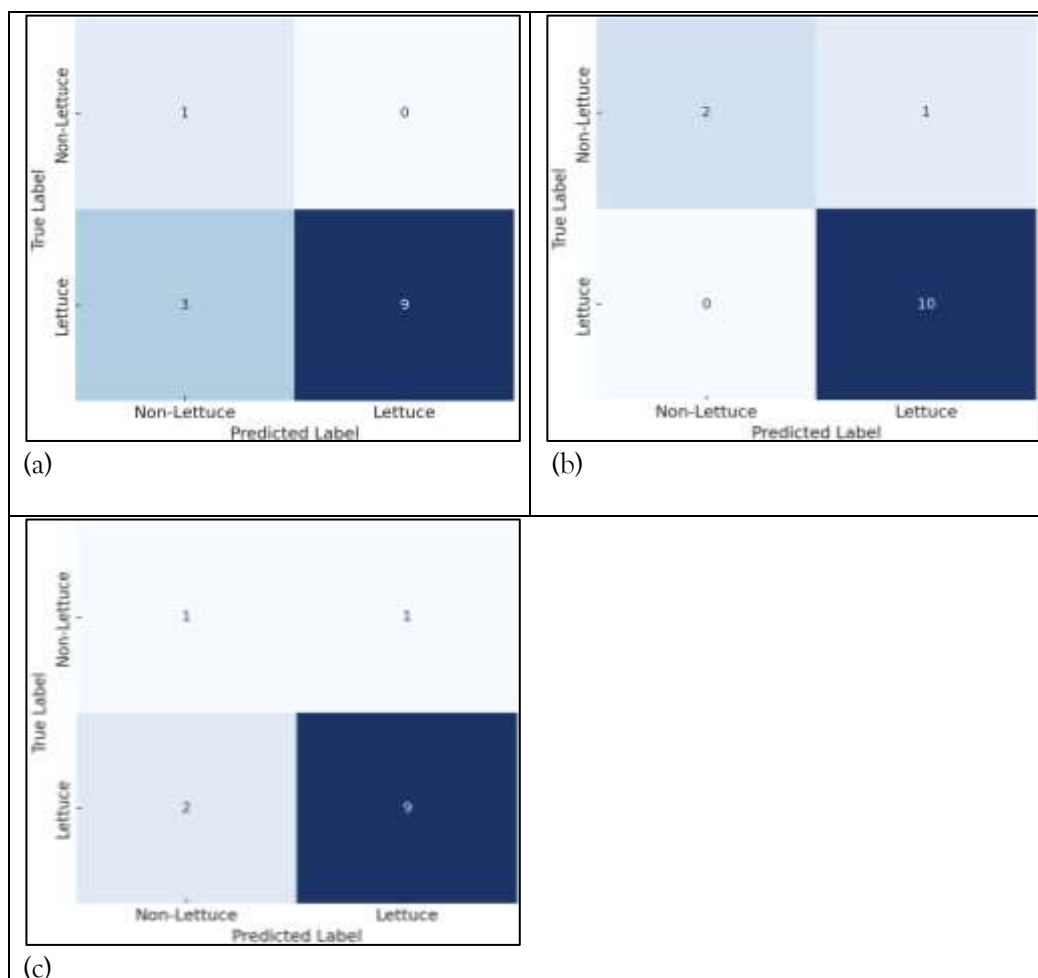
The classification accuracy of three CNN models was assessed in all three different scenarios representing different classification challenges. Various images were used in evaluating the CNN models as shown in Figure 1 including non-lettuce in Figure 1(a), healthy in Figure 1(b), and diseased lettuce in Figure 1(c). The first scenario focused on identifying the difference between lettuce leaves and non-lettuce, ensuring the models could handle unfamiliar images. The second scenario was distinguishing images of diseased, healthy, and non-lettuce. The final scenario involved identifying a specific lettuce leaf disease and healthy leaves. Confusion matrices were used to analyze correct and incorrect classifications, allowing a comprehensive comparison of model strengths and weaknesses across test scenarios [11] [16].



**Figure 1.** Sample dataset in comparing CNN Models; (a) non-lettuce, (b) healthy lettuce, and (c) diseased lettuce

#### 3.2.1. Test Scenario 1

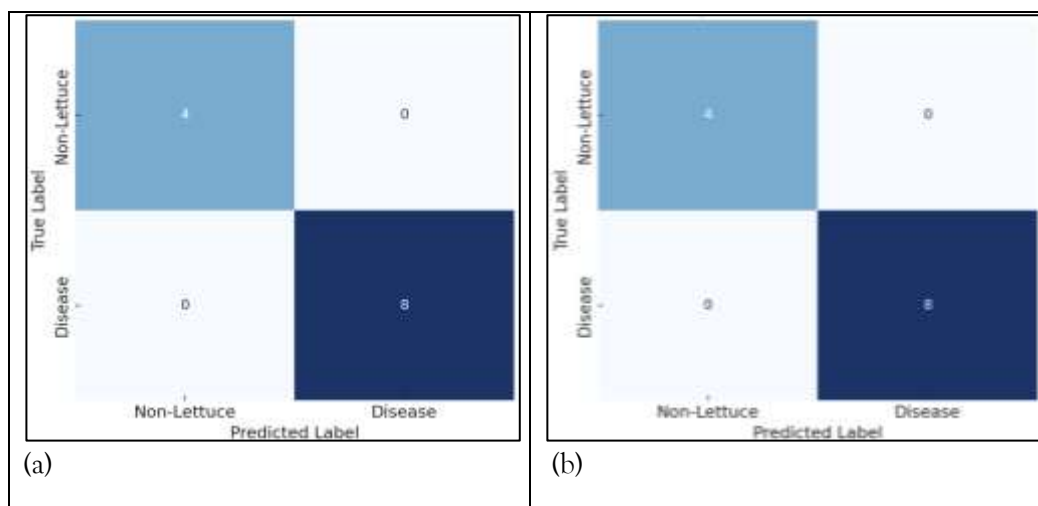
The first test scenario involves the use of 10 lettuce and 3 non-lettuce images, including lettuce-like and an ambiguous image. As shown in Figure 2, the three CNN models have unique methods of classifying images. InceptionV3 in Figure 2(b) performed best with 92.30% accuracy. The model misclassified one lettuce-like image but correctly recognized all lettuce images. EfficientNet and ResNet50 both attained 76.92% accuracy, each misclassifying three images. Both struggled particularly with non-lettuce detections. EfficientNet showed inconsistency in non-lettuce detection. Overall, while all models successfully detected most actual lettuce leaves, InceptionV3 was far more reliable in rejecting non-lettuce images, whereas EfficientNet and ResNet50 had higher false positive rates in this scenario.

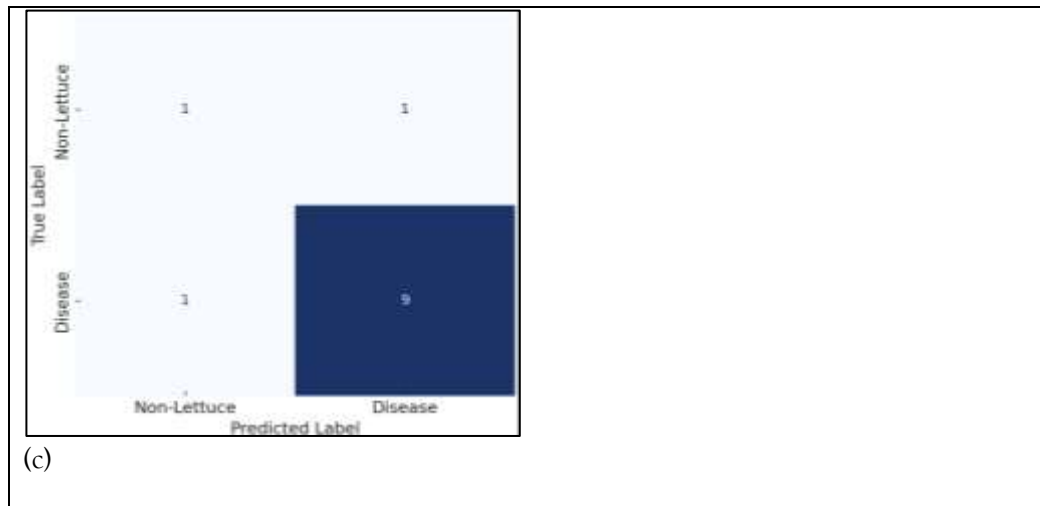


**Figure 2.** Classification accuracy of the CNN Models; (a) EfficientNet, (b) Inception V3, and (c) ResNet50 using lettuce and non-lettuce images

### 3.2.2. Test Scenario 2

The second test scenario focuses in evaluating the accuracy of the three CNN models based on disease detection using 12 images, which included 8 diseased and 4 non-lettuce with a diseased lettuce-like image. The classification performance of each CNN model is shown in Figure 2. Both EfficientNet in Figure 2(a) and InceptionV3 in Figure 2(b) achieved 100% accuracy. These two CNN models properly classified all 12 test images. ResNet50 in Figure 2(c) was far behind with only 83.3% accuracy. It accurately identified 100% diseased images but only identified 50% of healthy or lettuce like images. This indicates ResNet50's weakness in distinguishing healthy or lettuce like from diseased one.

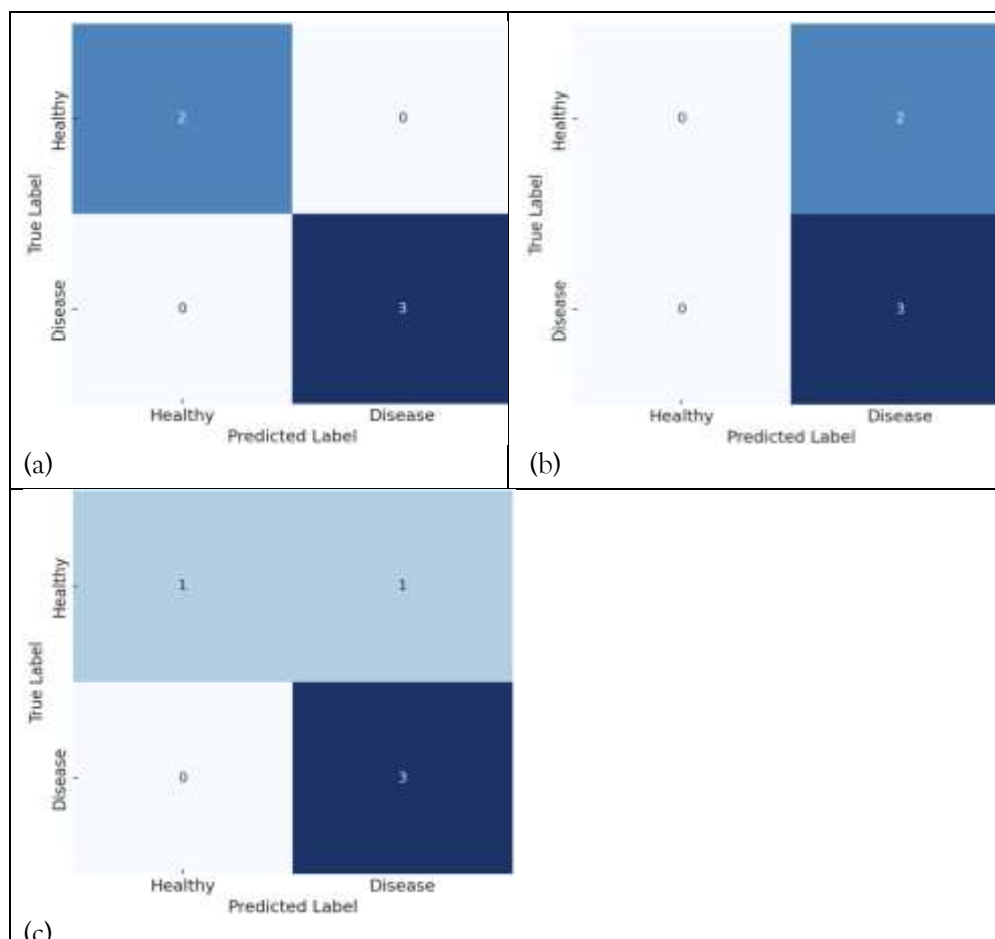




**Figure 3.** Classification accuracy of the CNN Models; (a) EfficientNet, (b) Inception V3, and (c) ResNet50 using diseased and non- lettuce

### 3.2.3. Test Scenario 3

The third test scenario utilized 2 healthy lettuce and 3 diseased lettuce specifically downy mildew as test images. As illustrated in Figure 4, the three CNN models have unique methods of classifying images. EfficientNet in Figure 4(a) achieved 100% accuracy, properly recognizing all healthy and diseased images without error. This shows that it is more effective in detecting the difference between healthy and diseased lettuce leaves. Figure 4(b) reveals that InceptionV3 accurately identified all of the diseased images, yet failed to identify any of the healthy lettuce. ResNet50 in Figure 4(c) performed effectively in classifying all the diseased leaves, but it made an error by classifying a healthy leaf as diseased. These results show that EfficientNet is robust and capable of classifying images evenly. InceptionV3, on the other hand, is too sensitive to disease, while ResNet50 made an insignificant error in classifying healthy leaves.



**Figure 4.** Classification accuracy of the CNN Models; (a) EfficientNet, (b) Inception V3, and (c) ResNet50 using specific lettuce leaf disease and healthy lettuce

Table 1 summarizes the classification accuracy of EfficientNet, InceptionV3, and ResNet50 across three test scenarios. EfficientNet had been more effective than InceptionV3 and ResNet50 for detecting diseases and classifying lettuce from non-lettuce, with an overall accuracy of 92.31%. This makes it the most reliable model for varied classification tasks involving lettuce leaf images.

**Table 1.** Summary of classification accuracy of the CNN models across three test scenarios

| CNN Model    | Classification Accuracy |                 |                 |         |
|--------------|-------------------------|-----------------|-----------------|---------|
|              | Test Scenario 1         | Test Scenario 2 | Test Scenario 3 | Mean    |
| EfficientNet | 76.92%                  | 100.00%         | 100.00%         | 92.31 % |
| InceptionV3  | 92.30%                  | 100.00%         | 60.00%          | 84.10 % |
| ResNet50     | 76.92%                  | 83.33%          | 80.00%          | 80.08 % |

#### 4) DISCUSSIONS:

The results from the three test scenarios highlight the importance of selecting an appropriate CNN model for lettuce leaf image classification. EfficientNet's consistent and excellent performance, especially its perfect accuracy in identifying diseases and differentiating between healthy and diseased leaves, suggests that it has a lot of potential for use in actual agricultural applications. Robustness is demonstrated by its ability to reliably classify both relevant and ambiguous images. On the other hand, InceptionV3 shown sensitivity to non-disease inputs, which may result in needless warnings in field situations, even though it was accurate in recognizing disease. Although ResNet50's moderate performance may make it less appropriate for applications requiring precision, it may still be able to meet more general categorization requirements. Overall, the results support the use of EfficientNet in smart farming systems by highlighting the fact that it provides a more reliable and balanced solution for tasks requiring accurate and consistent detection of lettuce leaf conditions.

#### 5) CONCLUSION:

In this study, the effectiveness of three well-known convolutional neural network (CNN) models such as EfficientNet, InceptionV3, and ResNet50 in detecting lettuce leaf diseases in hydroponic farming was compared. Based on the study, EfficientNet is the most dependable and consistent model for accurately and early lettuce leaf disease detection. EfficientNet's exceptional performance in both general and disease-specific lettuce recognition tests demonstrate the possibility for use in automated diagnostic applications. These applications can help small-scale hydroponic farmers by facilitating prompt interventions, reducing losses, and encouraging more sustainable farming practices.

Future research is recommended to increase the dataset's variability and local relevance to strengthen the model's robustness. Farmers will also find it easier to diagnose diseases if these models are included into web or mobile applications. To make sure that the developed diagnostic applications address real-world needs and challenges, collaboration with farmers and agricultural experts is also encouraged. Ultimately, the increasing hydroponic industry may benefit from enhanced productivity, food security, and sustainability with the use of strong CNN-based solutions, enabling the possibility to more resilient and productive urban farming in the Philippines.

#### 6) Acknowledgement:

The authors are thankful for the academic institution, research community, and agricultural practitioners who gave them helpful advice and assistance that helped them complete this study.

#### 7) REFERENCES:

Abbasi, R., Martinez, P., & Ahmad, R. Crop diagnostic system: A robust disease detection and management system for leafy

green crops grown in an aquaponics facility. *Artificial Intelligence in Agriculture*, 2023, 10, 1-12.

<https://doi.org/10.1016/j.aiia.2023.09.001>

- [1] Baranwal S., Khandelwal S., Arora A. Deep learning convolutional neural network for apple leaves disease detection. *SSRN Electron. J.*, 2019. <https://doi.org/10.2139/ssrn.3351641>
- [2] Chen, J., Chen, J., Zhang, D., Sun, Y., & Nanehkaran, Y. A. Using deep transfer learning for image-based plant disease identification. *Computers and Electronics in Agriculture*, 2020, 173,105393. <https://doi.org/10.1016/j.compag.2020.105393>
- [3] Ferentinos, K. P. Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, 2018, 145, 311-318. <https://doi.org/10.1016/j.compag.2018.01.009>
- [4] He, K., Zhang, X., Ren, S. and Sun, J. Deep Residual Learning for Image Recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2016, 770-778. <https://doi.org/10.1109/CVPR.2016.90>
- [5] Jasrotia, S., Yadav, J., Rajpal, N., Arora, M., & Chaudhary, J. Convolutional Neural Network Based Maize Plant Disease Identification. *Procedia Computer Science*, 2023, 218, 1712-1721. <https://doi.org/10.1016/j.procs.2023.01.149>
- [6] Khatri, L., Kunwar, A., & Bist, D. R. Hydroponics: Advantages and Challenges in Soilless Farming. *Big Data in Agriculture*, 2024, 6, 81-88. <https://doi.org/10.26480/bda.02.2024.81.88>
- [7] Mitra, D. Emerging plant diseases: research status and challenges. *Emerging trends in plant pathology*, 2021, 1-17. [http://doi.org/10.1007/978-981-15-6275-4\\_1](http://doi.org/10.1007/978-981-15-6275-4_1)
- [8] Mohanty, S. P., Hughes, D. P., & Salathé, M. Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*, 2016, 7, Article 1419. <https://doi.org/10.3389/fpls.2016.01419>
- [9] Naresh, R., Sagar, J., Beese, S., & Singh, M. Role of Hydroponics in Improving Water-Use Efficiency and Food Security. *International Journal of Environment and Climate Change*, 2024, 14, 608-633. <https://doi.org/10.9734/IJECC/2024/v14i23976>
- [10] Powers, D. M. Evaluation: From precision, recall and F-measure to ROC, informedness, markedness & correlation. *Journal of Machine Learning Technologies*, 2011, 2(1), 37-63. <https://arxiv.org/abs/2010.16061>
- [11] Pratama, I. Y., Wahab, A., & Alaydrus, M. Deep Learning for Assessing Unhealthy Lettuce Hydroponic Using Convolutional Neural Network based on Faster R-CNN with Inception V2. *Fifth International Conference on Informatics and Computing (ICIC)*, 2020. <https://doi.org/10.1109/icic50835.2020.9288554>
- [12] Resh, H. *Hydroponic Food Production: A Definitive Guidebook for the Advanced Home Gardener and the Commercial Hydroponic Grower*. CRC Press, 2022. <https://doi.org/10.1201/9781003133254>
- [13] Robinson, G. M. Global sustainable agriculture and land management systems. *Geography and Sustainability*, 2024, 5 (4), 637-646. <https://doi.org/10.1016/j.geosus.2024.09.001>
- [14] Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2016, 2818-2826. <https://doi.org/10.1109/CVPR.2016.308>
- [15] Sokolova, M., & Lapalme, G. A systematic analysis of performance measures for classification tasks. *Information Processing & Management*, 2009, 45(4), 427-437. <https://doi.org/10.1016/j.ipm.2009.03.002>
- [16] Tan, M., & Le, Q. V. EfficientNet: Rethinking model scaling for convolutional neural networks. In *Proceedings of the 36th International Conference on Machine Learning (ICML)*, 2019, 6105-6114. <https://arxiv.org/abs/1905.11946>
- [17] Viana, C. M., Freire, D., Abrantes, P., Rocha, J., & Pereira, P. Agricultural land systems importance for supporting food security and sustainable development goals: A systematic review. *Science of the Total Environment*, 2022, 806, Part 3, 150718. <https://doi.org/10.1016/j.scitotenv.2021.150718>
- [18] Yapp, E., Nazarina, J., Lee, L., Chooi, Y., Chen, C. Urban farming: the challenges of hydroponic and vertical farming in Malaysia. *Cogent Food & Agriculture*, 2025, 11(1), 2448601. <https://doi.org/10.1080/23311932.2024.2448601>
- [19] Zhao, Y., Chen, Z., Gao, X., Song, W., Xiong, Q., Hu, J., & Zhang, Z. Plant Disease Detection Using Generated Leaves Based on DoubleGAN. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, 2022, 19(3), 1817-1826. <https://doi.org/10.1109/TCBB.2021.3056683>