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Resnet-Based Approach For Detection And Classification Of Plant Leaf Diseases

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Abstract

Plant diseases may cause large yield losses, endangering both the stability of the economy and the supply of food. Convolutional Neural Networks (CNNs), in particular, are deep neural networks that have shown remarkable effectiveness in completing image categorization tasks, often outperforming human ability. It has numerous applications in voice processing, picture and video processing, and natural language processing (NLP). It has also grown into a centre for research on plant protection in agriculture, including the assessment of pest ranges and the diagnosis of plant diseases. In two plant phenotyping tasks, the function of a CNN (Convolutional Neural Networks) structure based on Residual Networks (ResNet) is investigated in this study. The majority of current studies on Species Recognition (SR) and plant infection detection have used balanced datasets for accuracy and experimentation as the evaluation criteria. This study, however, made use of an unbalanced dataset with an uneven number of pictures, organised the data into several test cases and classes, conducted data augmentation to improve accuracy, and—most importantly—used multiclass classifier assessment settings that were helpful for an asymmetric class distribution. Furthermore with all these frequent issues, the paper addresses selecting the size of the data collection, classifier depth, necessary training time, and assessing the efficacy of the classifier when using various test scenarios. The Species Recognising (SR) and Identifying of Health and Infection Leaves (IHIL) tasks in this study have shown substantial improvement in performance for the ResNet 20 (V2) architecture, with Precision of 91.84% & 84.00%, Recall of 91.67% and 83.14%, and F1 scores of 91.49% & 83.19%, respectively.

Keywords: Plant Diseases, ResNet, Convolutional Neural Network (CNN), Species Recognition, Species Recognition (SR), Natural Language Processing (NLP), Economic Stability, Class Distribution, Datasets.

I.INTRODUCTION

Plant diseases negatively impact agricultural productivity. Plant diseases will become more widespread if they are not detected in a timely way [1]. Because effective prevention and treatment of plant diseases depend on early detection, plant diseases play a significant role in agricultural management and decision-making. In recent years, the identification of plant diseases has become a crucial problem. Visible lesions or marks on leaves,

stems, blossoms, or fruits are often seen in plants that are diseased [2]. Every disease or pest issue often has a unique external pattern that may be used to detect abnormalities in a particular manner. Since many symptoms of plant illnesses may first be observed on the surface of the plant's leaves, [2, 3], plant diseases are often mainly recognised by examining the leaves of the plants.
Most of the time, forestry and agricultural professionals, or farmers using their own experience, identify fruit tree disease-carrying organisms on the spot [3, 4]. This method is difficult, time-consuming, and ineffectual in addition to being subjective. Unskilled farmers could make bad choices and use drugs recklessly throughout the identification process.
Conventional ReLU activation algorithms in deep neural networks are ineffective in addressing the vanishing gradient issue, whereas ResNet does [4, 5]. In some situations, neuron with negative inputs are limited in their ability to learn because they produce zero throughout training and stay dormant. As a ReLU version, the Leaky ReLU method of activation was presented as a way around this restriction. For negative input values, a leaky ReLU adds a little negative slope (often a small percentage, like 0.01) [5, 6]. The gradient flow is ensured and neurons are kept from being completely dormant by the modest negative slope, which permits the activation to remain non-zero for negative inputs. The issues in leaf disease identification are well addressed by the combined use of ResNet and Leaks ReLU, known as Leaky ReLU ResNet.
Leaky ReLU activations are included into the model to overcome the dying ReLU issue and provide smooth gradients during training, ensuring superior learning in the face of negative inputs. The leaky ReLU Res Net model training and evaluation are made possible by the Plant Village dataset [6, 7]. The collection, which consists of high-resolution leaf photos of various crops and illnesses, reflects the variety of leaf disease trends seen in actual agricultural environments.
Along with productivity and quality, contamination of the environment will result in needless financial losses. As a response to these issues, [8], the use of image processing methods for the identification of plant diseases has grown in popularity.
The general approach of detecting plant diseases using traditional picture identification and processing technologies is shown in Fig. 1. K-means clustering was used to separate the lesions into areas. Using any combination of the worldwide Colour Harmonic (GCH), Colour Coherent Vector (CCV), Local Binary Patterns (LBP), [9], or Complete Locally Binary Pattern (CLBP), the chromatic and textural attributes of the apple spots were retrieved. An enhanced Supported Vector Machinery (SVM) was used to identify and identify three different forms of apple illnesses, with a 93% precision for classification [10, 11].
With billions of people globally dependent on agriculture for nutrition and nourishment, agriculture is the foundation of humanity's civilization. However, the advent and spread of diseases of plants poses serious difficulties to agricultural yield. Plant diseases brought on by pathogens, such as viruses, fungi, bacteria, and other elements, [11, 12], may result in significant production losses and jeopardise the stability of the food supply and the economy.
For efficient crop management, early and precise diagnosis of diseases of leaves is essential to reducing their effects and ensuring prompt treatments [13, 14]. Manually recognising and classifying diseases of plant leaves takes a lot of time and work, and it is often vulnerable to subjectivity and human mistake. The accuracy and scalability of leaf disease detection methods were constrained by the hands-on examination of agricultural specialists in traditional methods. Moreover, these methods have difficulty managing the massive amounts of data produced from different agricultural fields and geographical areas around the globe.
The main issue with using cameras such as digital Charging Couple Devices (CCD) photographic equipment, mobile recording devices, cameras and portable spectroradiometers, etc., is gathering pertinent photos [15, 16]. To provide a more precise categorization result, the pre-processing stage filters out photos with irrelevant data and resizes, demonises, and segments the relevant images. Overfitting may occur when a classifier over fits the original notion by modelling noise and error found in the data.
One known solution suggested by researchers to address this issue is data augmentation, which is the expansion of the existing dataset by the addition of artificially created data. The photos' extraction of features process comes next [16]. Consequently, it is crucial to achieve intelligent, quick, and precise plant leaf disease detection.

Fig. 1 Conventional Image Recognition Techniques.

1.1Objectives of the study

- Develop methods for locating the sick spots and locations of interest within the leaf photos.
- To improve the training dataset's variety and the model's capacity to generalise to new, unknown data, use data augmentation approaches.

II.LITERATURE REVIEW

(Loganathan, P., 2021) [17] Every nation's foundation is agriculture, however the more different kinds of agriculture produced, the more the modern environment demands for progress. Consequently, traditional agriculture has a number of issues and is unpredictable in the past. A collection of plant leaf veins photos from cucumber and rose leaves is presented in this research. Because the cucumber and rose leaves have a primary vein with branching veins, they are classified as dicots. Next, an entirely novel the residual effect neural network (ResNet) type models were applied to each of the dataset's numerous instances, which included 64x64, 32x32, pixel a single-channel centre-focused pictures, for the purpose of identifying the group.
(Ding, R., Qiao, Y., 2022) [18] Apple leaf diseases are common and vary widely, which has a negative impact on the quantity as well as the quality of apples produced. The foundation for managing common leaf diseases in apple trees during their entire life cycle, enhancing apple quality, and guaranteeing high-quality apple yield is the timely and precise detection of apple leaf diseases. Two enhanced approaches that include the ResNet18 network are offered towards the classification of apples leaf diseases in an effort to increase the accuracy of the apples leaf disease detection model.
(Sri, V. S., Sailu, V. H., 2023) [19] Distinct approaches have been used in agriculture recently to solve distinct issues. These approaches include, but are not limited to, ways to increase agricultural output, identify pests that are hiding, and use effective pest control measures. This research presents a unique approach that employs drones to identify plant leaf diseases in agricultural areas. We ensure complete coverage of the whole region by using high-resolution cameras on drones to capture exact photographs of plant leaves. The early diagnosis of infections is made possible by the use of these photos as datasets for Convolutional Neural Networks (CNN), Res's net, and ReLu Deep Learning algorithms.
(Luo, Y., Sun, J., Shen, J., 2021) [20] Apple illnesses cost Chinese fruit producers a great deal of money. Apple illnesses may be correctly detected early on to stop the disease's progress and save manufacturing costs. The importance of disease characteristics in complex environments, however, is very low, and there is a significant amount of extremely fine variation across the many illnesses that affect apples. As a result, traditional feature extraction techniques lose their ability to discriminate between diseases. This research proposes a multi-scale feature fusion-based apple disease classification approach to address these issues.
(Liang, S., & Deng, X. 2022) [21] The conventional method of identifying rice disease of the leaves relies on artificial design elements and has a lengthy time and poor accuracy. The use of a depth residual system-based networks for the identification of rice leaf diseases is suggested by this study. A kernel function-based nonlinear support vector machine (SVM) is used to make the informational sampling linearly divisible. The ResNet 101 network serves as the network's foundation. The plant Development data set is sent to parameters that are learned in the ResNet 101 network to complete the construction. The model's average rate of recognition after verification was 99.89%, indicating that the network has become more adept at balancing identification accuracy requirements with network efficiency and lightness.
(Patidar, S., Pandey, A., 2020) [22] India's economy now relies heavily on agricultural production and farming outputs. Because it is rather common for plants to be attacked by certain bacterial or fungal diseases, recognising & detecting illnesses in crops or plants becomes quite crucial. This might have disastrous impacts on both the amount and quality of products produced, or even production as a whole, if it cannot be resolved as soon as possible. Rather of relying just on visual sighting and identification, machine learning ideas may undoubtedly assist achieve this aim more efficiently.

III.Methodology

This section covers the dataset, the arrangement of the data set, the pre-processing of the photos, & the classification approach used for the purpose of identifying specific species and health conditions.

3.1Dataset

For this, a data collection containing segmented leaf pictures of twelve distinct species of plants was used. The dataset's variability is heightened by the diversity of species it contains. A Nikon D5300 cameras was used to take pictures in a cleverly included space [23]. It has 4503 photos, of which 2278 show leaves in good health and 2225 show leaves with various disorders. The data set's details are shown in Table 1. Figure 2 displays an example of a sick and healthy leaf for every species.

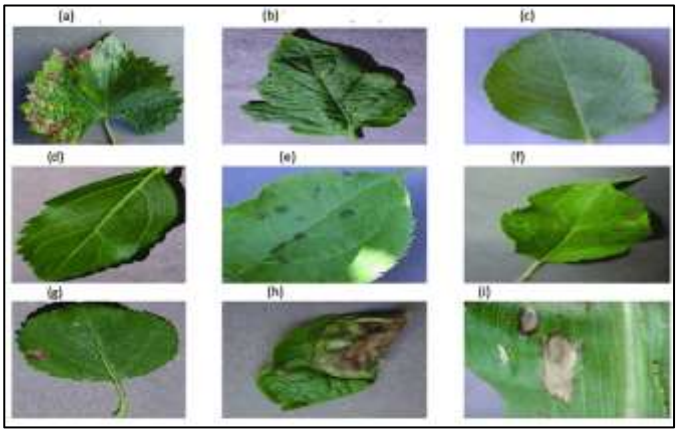

Fig. 2 Leaf imagine sample of each species, both healthy and unhealthy.

Table 1 The quantity of graphic samples included in the dataset.

Plant species	**Number of images**	**Plat species**	**Number of images**
(Mangifera indica)	H:56, I:236	**(Jatropha Curccas)**	H:169, I:564
(Terminalia arjuna)	H:56, I:260	**(Pongamia Pinnata L)**	H:469, I:681
(Alstonia scholaris)	H:49, I:659	**(Ocimum Basilicum)**	H:697, I:659
(Pasidium guajana)	H:26, I:552	**(Citrus Limon)**	H: 596, I:496
(Bael)	H:89, I:594	**(Piatanus Orientalist)**	H:569, I: 269)

3.2Classification

DL structures, including Alex Net, Google Nets, ResNet, Vision V3, Fusion V4, VGG-16, VGG-19, and so on, were extensively used for classification purposes since a number of criteria determine which DL model is the most appropriate for a certain application Figure 3.

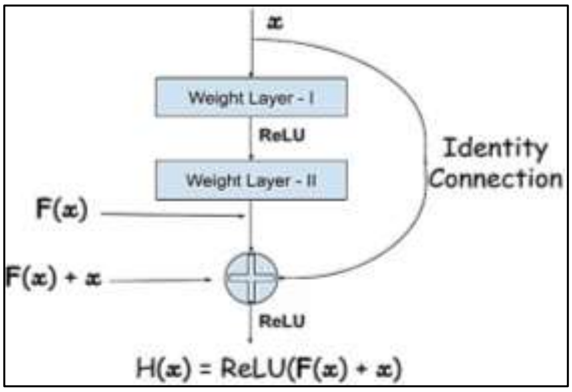

Fig. 2 Relative learning is one of the fundamental components of residual network version 2.

IV.RESULTS

The results of the performance metrics (macro-average) values for every test scenario are listed in Table 2. Because macro-averaging gives each class the same weight, it prevents Bael & Basil classes from being given preference for the SR job [24]. For symmetric class distributions, where the cost of true positives and false negatives is almost equal, accuracy is the better performance indicator. However, for asymmetrical class patterns of distribution, the performance level is more accurately represented by accuracy, recall, and F1 score.

$$Accuracy = \frac{\sum_{t=1}^{n}(tp_t+tn_t)}{\frac{\sum_{t}^{n}(tp_t+tn_t+fp_t+fn_t)}{n}} \quad ....1$$

$$precision = \frac{\sum_{t=1}^{n} tp_t}{\frac{\sum_{t=1}^{n}(tp_t+fp_t)}{n}} \ldots\ldots.2$$

$$Recall = \frac{\sum_{t=1}^{n} tp_t}{\frac{\sum_{t=1}^{n}(tp_t+fp_t)}{n}} \ldots\ldots.3$$

$$F1\ score = \frac{2\times(precision\ \times Recall)}{Precision+Recalll} \ldots\ldots.4$$

The F1 score is the harmonised averaged of memory or accuracy. It offers a more precise and equitable evaluation that more accurately represents the performance of the DL model. Consequently, the F1 score received higher priority in our analysis. ResNet 20 (V2) demonstrated highest accuracy & F1 Score among all the test examples.

Table 2 Results for Every Test Scenario.

Test cases	Task	Accuracy %	Precision %	Recall %	F1 Score %
U11_R12	SR	98.65	49.59	46.98	98.65
U13_R21	SR	46.92	46.92	46.36	56.32
U15_R23	SR	56.26	89.16	66.49	65.19
U18_R25	SR	49.32	14.56	29.46	24.98
U19_R29	IHIL	56.19	59.68	46.98	26.49

The comparative findings comparing the proposed & current methodologies are shown in Table 3. The results of this study showed that the recommended LRLR methodology had a greater success rate when compared to the other methodologies already in use [25].

Table 3 Comparative Outcomes.

Accuracy %	Precision %	Recall %	F1-Score %	Specificity %
90.56%	96.48%	97.65%	90.68%	89.69%
93.59%	96.48%	86.98%	89.56%	94.65%
95.48%	91.64%	89.56%	97.65%	86.55%
90.79%	96.49%	86.98%	82.69%	89.69%
94.65%	93.63%	95.69%	92.69%	95.69%

V.DISCUSSION

This article describes the detection of plant health conditions and the identifying of species under various experimental conditions. A comprehensive analysis of the DL models' performance was provided by means of multiclass classification-based performance indicators. There was a minimum of 77 pictures and an overall average of 345 pictures per class in the image of the leaf database [26]. Methods such as under sampling and data supplementation have been used in order to rectify the imbalanced dataset and broaden the training data set. The dataset with artificial pictures added performed better than the dataset that included fewer photographs in terms of identifying health conditions and recognising species, with an F1 Score that was 2.06% higher and 0.6% higher, respectively. ResNet classification may assist to offset accuracy loss in deeper networks. ResNet 20 (V2) yielded the greatest F1 Scores for SR and IHIL, 91.49% and 83.19%, respectively.

Using Support Vector Machines (SVM) and Simple Linear Iterative Clustering (SLIC) when analysing complicated background images of tea leaf diseases, researchers were able to obtain a significant number of accurate images of these diseases, with 98.5% accuracy, 96.8% precision, 98.6% recall rate, and 97.7% F1 score [27]. The results shown that the technique can successfully recover leaves of tea from complicated backgrounds with substantial.

VI.CONCLUSION

Conversely, ResNet 20 (V2) yielded an F1 Score that was 16% higher than Alex Net as the research suggests that ResNet is better suited for high-performance applications, whereas the Alex Net is better suited for applications that operate in real time. The investigation and analysis shed light on how the number of courses, the number of images in the data set used for training, the depth of the classifier, and computation time affect the performance of the deep learning approach in the SR and IHIL settings. Furthermore, the method provides a practical means of managing an uneven data collection. The research does not consider any concept of power

consumption, memory utilisation, etc. in this particular setting. Additionally, there is room to examine ways to further improve the process of detection accuracy.
The self-learning properties of deep learning-based algorithms for classification may be further improved in the context of smart agriculture by adding primary datasets to a classifier that was learned using secondary datasets. Future both indoors and outdoors intelligent farming systems must be trained on a large dataset consisting of both primary and secondary data collected in a range of regulated and uncontrolled situations in order to achieve fully automated operations. It is also possible to investigate if improving the model's performance using more supplemented data. Larger and more balanced datasets have been linked to improved accuracy in SR & IHIL, according to some study. Farmers' yields will soon increase thanks to computers vision-based medical condition detection, analysis, and real-time treatment for plant diseases.
In the setting of smart farming, a superior performance metric for plant phenotyping may be offered by the algorithm for deep learning based on ResNet. Including many classes and evaluating the effectiveness of the classifier utilising multiclass assessment the parameters reduces false alarms and increases prediction robustness. The current work has an opportunity to provide an ideal method for smart farming systems through a variety of techniques, including adjusting and growing the dataset, generating new test cases, preserving the classifier's thoroughness with that of its initial training scenarios, experimentation with various training phases, and utilising multiple classes investigation variables for the performance evaluation.

Future work
Future research aims to improve resilience by using comprehensive and broad dataset gathering to address the imbalance problems associated with a particular plant.

VII.REFERENCE

1. Q.-F. Wu, Y.-P. Chen, and J. Meng, “DCGAN-based data augmentation for tomato leaf disease identification,” IEEE Access, vol. 8, pp. 98716–98728, 2020.
2. B. Liu, C. Tan, S.-Q. Li, J.-R. He, and H.-Y. Wang, “A data augmentation method based on generative adversarial networks for grape leaf disease identification,” IEEE Access, vol. 8, pp. 102188– 102198, 2020.
3. M. Brahimi, K. Boukhalfa, and A. Moussaoui, “Deep learning for tomato diseases: Classification and symptoms visualization,” Appl. Artif. Intell., vol. 31, no. 4, pp. 299–315, May 2017.
4. M. Brahimi, M. Arsenovic, S. Laraba, S. Sladojevic, K. Boukhalfa, and A. Moussaoui, “Deep learning for plant diseases: Detection and saliency map visualization,” in Human and machine learning, Boston, BSN, USA: Springer, Jun. 2018, pp. 93-117.
5. A. C. Cruz, A. Luvisi, L. De Bellis, and Y. Ampatzidis, “Visionbased plant disease detection system using transfer and deep learning,” in 2017 Asabe Annu. Int. Meet., GEG, USA, Jul. 2017, pp. 16–19.
6. M. Brahimi, S. Mahmoudi, K. Boukhalfa, and A. Moussaoui, “Deep interpretable architecture for plant diseases classification,” in Signal Process.: Algorithms, Architectures, Arrangements, and Applications (SPA), POZ, POL, Jul. 2019, pp. 111–116.
7. C. DeChant, T. Wiesner-Hanks, S. Chen, E. L. Stewart, J. Yosinski, M. A. Gore, R. J. Nelson, and H. Lipson, “Automated identification of northern leaf blight-infected maize plants from field imagery using deep learning,” Phytopathology, vol. 107, no. 11, pp. 1426– 1432, Aug. 2017.
8. Shankar, K.; Zhang, Y.; Liu, Y.; Wu, L.; Chen, C.H. Hyperparameter tuning deep learning for diabetic retinopathy fundus image classification. IEEE Access 2020, 8, 118164–118173.
9. Gulshan, V.; Peng, L.; Coram, M.; Stumpe, M.C.; Wu, D.; Narayanaswamy, A.; Venugopalan, S.; Widner, K.; Madams, T.; Cuadros, J.; et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA 2016, 316, 2402–2410.
10. Qummar, S.; Khan, F.G.; Shah, S.; Khan, A.; Shamshirband, S.; Rehman, Z.U.; Khan, I.A.; Jadoon, W. A deep learning ensemble approach for diabetic retinopathy detection. IEEE Access 2019, 7, 150530–150539.
11. Narsaiah, C.; Manoj, P.; Raju, A.G. Study on Awareness and Assessment of Diabetic Retinopathy in Diabetic Patients Attending Ophthalmology Clinic at a Tertiary Care Hospital, Telangana State. J. Contemp. Med. Res. 2019, 6, K9–K13.
12. Bansal, P.; Gupta, R.P.; Kotecha, M. Frequency of diabetic retinopathy in patients with diabetes mellitus and its correlation with duration of diabetes mellitus. Med. J. Dr. Patil Univ. 2013, 6, 366.
13. Fong, D.S.; Aiello, L.; Gardner, T.W.; King, G.L.; Blankenship, G.; Cavallerano, J.D.; Ferris, F.L.; Klein, R. Retinopathy in diabetes. Diabetes Care 2004, 27, s84–s87.
14. Fiorani, F.; Schurr, U. Future Scenarios for Plant Phenotyping. Annu. Rev. Plant Biol. 2013, 64, 267–291.

15. Kaur, S.; Pandey, S.; Goel, S. Plants Disease Identification and Classification through Leaf Images: A Survey. Arch. Comput. Methods Eng. 2018, 26, 507–530.
16. Barré, P.; Stöver, B.C.; Müller, K.F.; Steinhage, V. LeafNet: A computer vision system for automatic plant species identification. Ecol. Inform. 2017, 40, 50–56.
17. Loganathan, P., & Karthikeyan, R. (2021). Residual Neural Network (ResNet) Based Plant Leaf Disease Detection and Classification. Turkish Online Journal of Qualitative Inquiry, 12(6).
18. Ding, R., Qiao, Y., Yang, X., Jiang, H., Zhang, Y., Huang, Z. ... & Liu, H. (2022). Improved ResNet Based Apple Leaf Diseases Identification. IFAC-PapersOnLine, 55(32), 78-82.
19. Sri, V. S., Sailu, V. H., Pradeepthi, U., Sai, P. M., & Kavitha, M. (2023). Disease Detection using Region-Based Convolutional Neural Network and ResNet. Data and Metadata, 2, 135-135.
20. Luo, Y., Sun, J., Shen, J., Wu, X., Wang, L., & Zhu, W. (2021). Apple leaf disease recognition and sub-class categorization based on improved multi-scale feature fusion network. IEEE Access, 9, 95517-95527.
21. Liang, S., & Deng, X. (2022, October). Research on rice leaf disease identification based on ResNet. In 2022 IEEE 6th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC) (pp. 1409-1413). IEEE.
22. Patidar, S., Pandey, A., Shirish, B. A., & Sriram, A. (2020). Rice plant disease detection and classification using deep residual learning. In Machine Learning, Image Processing, Network Security and Data Sciences: Second International Conference, MIND 2020, Silchar, India, July 30-31, 2020, Proceedings, Part I 2 (pp. 278-293). Springer Singapore.
23. Owomugisha, G.; Mwebaze, E. Machine Learning for Plant Disease Incidence and Severity Measurements from Leaf Images. In Proceedings of the 2016 15th IEEE International Conference on Machine Learning and Applications (ICMLA), Anaheim, CA, USA, 18 December 2016; pp. 158–163.
24. Pawara, P.; Okafor, E.; Surinta, O.; Schomaker, L.; Wiering, M. Comparing Local Descriptors and Bags of Visual Words to Deep Convolutional Neural Networks for Plant Recognition. In Proceedings of the 6th International Conference on Pattern Recognition Applications and Methods, Porto, Portugal, 24 February 2017; SCITEPRESS: Setúbal, Portugal, 2017; Volume 24, pp. 479–486.
25. Xiong, J.; Yu, D.; Liu, S.; Shu, L.; Wang, X.; Liu, Z. A Review of Plant Phenotypic Image Recognition Technology Based on Deep Learning. Electronics 2021, 10, 81.
26. Lee, S.H.; Chan, C.S.; Mayo, S.J.; Remagnino, P. How deep learning extracts and learns leaf features for plant classification. Pattern Recognit. 2017, 71, 1–13.
27. Zhang, S.; Zhang, C. Plant Species Recognition Based on Deep Convolutional Neural Networks. In Proceedings of the International Conference on Intelligent Computing, Liverpool, UK, 7 August 2017; Springer: Cham, Switzerland, 2017; pp. 282–289.