# Application for Plant's Leaf Disease Detection using Deep Learning Techniques

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**Abstract -** *Agriculture/farming is a significant source of income for farmers in poor countries, and yield estimation is a significant challenge for them. This may be performed by agricultural monitoring of the plant or crop to predict the disease of a certain kind of plant, which can help to prevent hunger and support our Indian farmers before harvesting any plant. As a result, we're going to show you how to use deep learning algorithms to anticipate plant disease in a reliable and broad approach. First, we'll look at the diseases that affect that particular plant, as well as the yield estimates made by the remote sensing community, and then we'll provide a solution based on some of the most current representation learning technologies. We'll use a dataset of nation-level graph leaves and their related diseases to build a train model using convolutional neural networks and conditional random field approaches, which will be combined with image processing. This popular topic in our country suggests that our plan will implement some competing tactics.*

***Key Words***: **CNN, agriculture, optimizers, RNN, neural networks, Feature extraction.**

## 1.INTRODUCTION

The problem is of financial, technological, and social relevance since the identification of plant leaves is a critical feature in preventing a disastrous outbreak within our nation and aiding our economy's growth. In India, we note that automated identification of plant leaf disease is a challenging and important research topic. The majority of plant diseases are caused or caused by bacteria, fungi, and many deadly harmful viruses that we cannot detect with our naked eye. To do so, we need technological aspects, as well as some experts in observing and identifying plant diseases using computational approaches such as computer vision, Artificial Intelligence, and so on. These diseases will destroy living plants, resulting in a scarcity of produce for us and putting the lives of farmers in jeopardy, which is also a social problem. This difficult task makes emerging-nation experts expensive and time-consuming.

## 2. LITERATURE SURVEY

Radial basis function networks (RBFN) and bit neural systems (KNN), for example, a specific probabilistic neural system (PNN), are widely used foundation work systems [13], which explores their similarities and differences. This research proposes another feedforward neural system model known as outspread premise probabilistic neural system (RBPNN) to avoid the colossal measure of hidden units of the KNNs (or PNNs) and reduce the preparation time for the RBFNs in order to [29] avoid the colossal measure of hidden units of the KNNs (or PNNs) and decrease the preparation time for the RBFNs (RBPNN). This new system model, in a sense, combines the benefits of the two prior models while keeping a strategic distance from their flaws. Finally, we use our unique RBPNN to the recognition of one-dimensional cross-pictures of radar targets (five different types of aircraft) (five sorts of an airplane). This automated [14] technique uses images from 'Plant Village,' a publically accessible plant picture resource, to identify illnesses on potato plants. The use of an SVM and a division approach resulted in illness categorization in more than 300 pictures with a normal accuracy of 95%. The ReliefF [36] method was used to separate 129 highlights at first, and then an SVM model was built utilizing the most important highlights. The results showed that image recognition of the four hay leaf diseases could be achieved, with a standard accuracy of 94.74 percent. Application programming incorporates several types of calculations [15]. One of the most important strategies for dividing imaging into bits and foundation is image inspection. The discovery of elements is one of the most important achievements in image investigation. The results show that the FC and FS approaches choose [35] highlights that are much more suitable than those selected by humans arbitrarily or using other methods. Another methodology is used to find the grape leaf illness recognizable proof or determination, such as a paper explaining the grape leaf disease [37] recognition from shading fanciful utilizing crossbreed keen framework, in that programmed plant sickness determination utilizing various fake astute methods. The availability of standard [39] methodologies for picture classification missions resulted in highlights, whose presentation had a strong impact on the overall findings. FE is a complex, time-consuming procedure that must be revised [16] whenever the issue or dataset changes. FE creates a costly effort that relies on expert knowledge and does not sum up correctly using this technique.

Then DL doesn't require FE, [38] since it can find the relevant highlights on its own via planning. [28] calculated relapse, Scalable Vector Machines (SVM), direct relapse, Large Margin Classifiers (LCM), and naturally observable cell automata are examples of CNN algorithms that coupled their model with a classifier at the yield layer. For kimplies grouping, the extricated estimates of the highlights are lower. The accuracy of k-implies grouping is better than that of other techniques. [17] For illness signs that can be identified, the RGB picture is used. The green pixels are detected after applying k-implies bunching systems, and then the changing limit esteem is obtained using Otsu's [40] approach. The shading co-occurrence approach is used to extract the components. K-implies grouping, SVM, is a significant image preprocessing [18] used for the identification of leaf diseases. This procedure might help to pinpoint the exact site of leaf disease. Image obtaining, picture pre-preparing, division, include extraction, and grouping are among the [31] five stages for leaf sickness ID. In terms of both principle and application, CNN is a key example acknowledgment technique [41]. In contrast to the preferred way over ZCA - Whitening procedure to reduce the connection of information, the inventive method enhances the depth [19] learning power of CNNs. Using histogram management to amplify affected tissue while masking non-influenced tissue [20]. Then, utilizing component naming, a fluffy C-mean bunching algorithm is done to extract spectacular sickness features. In the phase of malady characterization, shading, [42] shape, and size data are taken care of by the back-engendering neural system. Highlights, such as the shade histogram, surface, or edge-based approaches [21], are used to find homogeneous areas in a picture. There are two types of picture division tactics: controlled and solo. The properties of several places in an image are predefined in the controlled [43] division approach, while there is no such data in solo division. Parting blending procedure is included in unaided computations. Cotton Diseases Control has been created as a dynamic framework in a BP neural system. Cotton foliar diseases disclosed [22] a strategy for classifying cotton maladies on a regular basis. Include extraction was done using Wavelet change vitality, and order was done with Support Vector Machine. The fluffy element picking approach fluffy bends (FC) and surfaces (FS) - is presented in the previous [44] study to identify highlights of the cotton sickness leaf picture. The frameworks presented try to [23] protect photos taken in common locations against changing separations. This makes the framework more durable in a variety of climatic conditions, and frameworks [33] have been proposed for identifying Alternaria, Bacterial Leaf Curse, and Myrothecium infections on cotton leaves. The [46] shots were taken using a high-tech camera, and the images were smoothed using image pre-processing techniques. Then, to isolate the illness location from the foundation, image division algorithms are used to photographs. The significant highlights are used to form the system that completes the characterisation, and the [45] highlights are separated from these portioned components. The Color Co-event Method is the process used to obtain the current set. Neural networks are used to identify disorders in leaves in a pre-programmed manner [24]. If [47]there should be an occurrence of steam, and root problems, the strategy supplied may essentially enhance a correct discovery of the leaf, and is by all accounts a considerable methodology, spending lower quantities of work in calculating. [48]An upgraded histogram division strategy for detecting limit naturally and correctly is provided in image division. Meanwhile, to improve the precision and insight edge division plans, the territorial development technique and real nature image preparation are merged with this [25] framework. Furthermore, there are four parts[49] that detail this structure: Disease Recognition System, improved histogram division technique Multi-selection intelligent image division methods based on Multiple Linear Regression. The unaided eye perception technique is often used in the creation process to determine disease severity, but results are subjective [26] and it is irrational to expect to accurately evaluate infection severity. To improve exactness, a matrix tallying technique may be utilized, although this strategy has an unmanageable activity process and is tiring. In rural research, image processing innovation has resulted in significant advancement. [50] A robotized framework has been developed to detect and describe sugarcane growths infection using calculations such as the chain code technique, the bouncing box method, and minute research. The developed processing system is divided into four primary stages. First, a color transformation structure for the input RGB image [1] is created; this RGB is then converted to HSI since RGB is used for color generation and is a color descriptor. Then, using a specified threshold value, green pixels are masked and deleted, the image is segmented, and the necessary segments are extracted, and finally, texture statistics are produced. derived from SGDM matrices Finally, the presence of diseases on the plant bread is assessed. In this system, machine vision algorithms [2] are used to overcome the challenges of extracting and analyzing information from tobacco leaves, which include color, size, shape, and surface texture. The results of the tests show that this method is a viable method for extracting tobacco leaf characteristics and that it might be used for automated classification of tobacco leaves. Pixels with 0 red, green, and [3] blue components, as well as pixels on the infected cluster's perimeter, are completely erased. This is beneficial since it provides more exact sickness classification and cuts processing time in half. The color format of the infected cluster is changed from RGB to HSI. The existence of diseases on the plant leaf will be classified and discovered. The first step consisted of capturing RGB images of leaf samples [4]. The following is a step-by-step procedure: Acquire an RGB image; transform the input image to a color space; segment the components; get the required segments; [27] The texture characteristics are computed, and the neural networks are configured for recognition. The raw images are divided into two groups: training and test. The remaining photographs are used for testing and 360 symptom and 120 healthy shots are selected for training [5]. To minimize overfitting, the training dataset is divided into training data (80%) and validation data (the remaining 20%). (20 percent ). 20% of the total Thus, the training dataset has 960 samples, the validation dataset contains 240 samples, and the test dataset contains 419 samples. We looked at detectors such as the Faster Region-Based Convolutional Neural Network (Faster RCNN), Region-based [6] Fully Convolutional Networks (RFCN), and Single Shot Multibox Detector (SSD) in this post (SSD). Depending on the application or need, each component of the architecture should be able to be integrated with any feature extractor. The model's first component (features extraction), which was the same for both the full-color and gray-scale approaches, consisted of four Convolutional layers with Relu activation functions, each followed by a Max Pooling layer. Appropriate datasets are required at all stages of object recognition research, from the training phase through the evaluation of recognition algorithms' performance [8]. Images downloaded from the internet came in a variety of formats, with varying resolutions and quality. Final images intended to be used as dataset for deep neural network classifier were preprocessed in order to attain consistency in order to get better [47] feature extraction. Initially, picture segmentation based on dge detection is performed, followed by image analysis and disorder classification [9] using our proposed Homogenous Pixel Counting Technique for Cotton Diseases Detection (HPCCDD) Algorithm. The goal of this research is to use an image analysis technique to determine the disease-affected section of cotton leaf sport. Five rounds of anisotropic diffusion enhance it, allowing it to retain the knowledge of the afflicted area. Anisotropic diffusion is a [10] extension of this diffusion process; it produces a family of parametrized images, but each one is a combination of the original image and a filter based on the original image's local content. Many alternative versions of CNNs have been devised for image recognition applications [11], and they have been successfully employed to solve tough visual imaging issues. The RGB images of citrus leaves are converted to color space representations [12]. The purpose of color space is to make specifying colors easier in a uniform, universally accepted manner.

## 3. ARCHITECTURE

**Step 1:** Determine which data analytics problems have the most potential for the firm.

**Step 2:** Choose the appropriate data sets and variables.

**Step 3:** Gathering vast amounts of structured and unstructured data from many sources.

**Step 4:** Cleaning and checking the data to ensure its accuracy, completeness, and consistency.

**Step 5:** Developing and using models and algorithms to utilize huge data repositories.

**Step 6:** Identifying patterns and trends in the data.

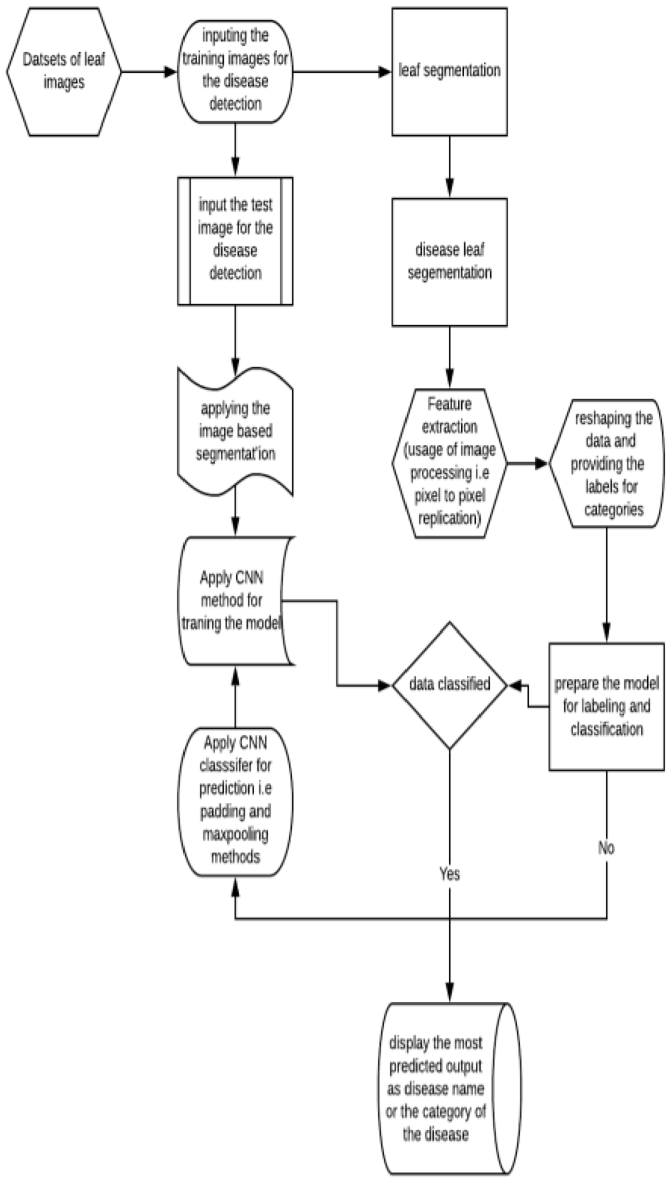
**Step 7:** Analyzing the information to find solutions and opportunities.

**Step 8:** Using visualization and other ways to communicate outcomes to stakeholders.

**Step 9:** First, the photographs from the dataset are read, converted to arrays, and labeled.

**Step 10 :** to resize the photos.

**Step 11:** Make the pickle files for later use.




**Step 12:** Reshaping the data in order to make it compatible with the model. Model compatibility requires converting labels to categories. Convolution, carpooling, and thick layers are used to create the neural network.

**Step 13:** 15% shuffling validation data is used to fit the model.

**Step 14:** Upload the model to the pipeline. Using test data to evaluate the model The trained model is sent to the server, and the model is deployed.

**Step 15:** Now that the test data has been entered into the website server, the data will be sent to the trained neural network, and the model will be created. A sample picture is predicted.

**Step 16:** The customer will get the disease's name through the front end.

## 4. ALGORITHM CORRESPONDING TO TRAINING PHASE

**Step 1:** The first layer to extract features from an input image is convolution.

**Step 2:** The number of pixels that move across the input matrix is called the stride. When the stride is one, the filters are shifted one pixel at a time.

**Step 3:** Padding: Filters don't always match the input image perfectly. There are two possibilities: • Make the picture fit by padding it with zeros (zero-padding). • Remove the part of the image where the filter didn't work. This is known as valid padding, because it keeps just the legitimate parts of the image.

**Step 4 :** For a non-linear operation, use a Rectified Linear Unit. (x) = max(0,x) is the outcome (0,x).

**Step 5:** Pooling Layer: When the images are too large, this section would restrict the amount of parameters. Spatial pooling, also known as subsampling or down sampling, reduces the dimensionality of each map while keeping the important data. Step 6: Fully Connected Layer (FC Layer): We converted our matrix to a vector and sent it into a fully connected layer, similar to a neural network.

## 5. TECHNICAL SUSTAINABILITY

Viticulture (the production of grapes, Vitis vinifera) is one of India's most profitable agricultural enterprises. Grapes may be found throughout Western Asia and Europe. Fruit is eaten raw or juiced, fermented into wines and brandies, and dried into raisins. Grapes also contain medicinal properties that may help with a variety of diseases. During the developing and fruiting stages, grapes need a hot and dry environment. It may be grown successfully in temperatures ranging from 150 to 400 degrees Celsius. Fruit set and, as a result, berry size are limited by temperatures over 400°C during fruit growth and development. Low temperatures below 15 degrees Celsius, combined with advance trimming, stymie budbreak, leading in crop loss. Grapes may be grown in sand loams, red sandy loams, sandy clay loams, shallow to medium black soils, and red loams, among other soil types. Downy mildew, powdery mildew, and anthracnose can cause significant crop losses in grapes. When downy mildew attacks the clusters before fruit set, the losses may be fairly significant. The whole cluster rots, dries out, and falls down [16]. Plant disease is one of the leading causes of production loss and quality degradation. The main technique used in practice for detecting and diagnosing plant diseases is experts' naked eye inspection. In large farms, this method is highly expensive and time consuming. Furthermore, in certain impoverished countries, farmers may have to travel long distances to contact professionals. Changing the pruning schedule and spraying various fungicides are used to cure diseases. Observations made during a research at the NRCG in Pune show that precision farming, or using information technology to make decisions, has improved crop yield and quality. This is why our notion is a game-changing technology. It would eliminate the need for farmers to travel long distances to visit professionals since all they would need is their phone. This would also explain our paradigm's long-term viability. Profitable businesses would continue to use our system for long periods of time, making it incredibly cost-effective and long-term.

## 6. Comparison with existing models in terms of Technology, cost and feasibility

Model: "sequential"

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv2d (Conv2D) | (None, 254, 254, 32) | 896 |
| conv2d_1 (Conv2D) | (None, 252, 252, 32) | 9248 |
| max_pooling2d (MaxPooling2D) | (None, 31, 31, 32) | 0 |
| conv2d_2 (Conv2D) | (None, 29, 29, 32) | 9248 |
| conv2d_3 (Conv2D) | (None, 27, 27, 32) | 9248 |
| max_pooling2d_1 (MaxPooling2 | (None, 3, 3, 32) | 0 |
| activation (Activation) | (None, 3, 3, 32) | 0 |
| flatten (Flatten) | (None, 288) | 0 |
| dense (Dense) | (None, 256) | 73984 |
| dense_1 (Dense) | (None, 4) | 1028 |

Total params: 103,652
Trainable params: 103,652
Non-trainable params: 0

Chart -1: Model Summary

There are a few documented use case scenarios where grape producers may keep an eye on their leaves for disease. The most common one requires personally bringing a farming consultant or an expert to your form to inspect the leaves and provide a judgment. This method is exceedingly costly, time-consuming, resource-intensive, and prone to errors. In general, using any technology and consulting experts will result in a large sum of money being invested by either the farmer or the government because building a prototype costs a lot of money. For example, governments plan to give farmers money for irrigation, pesticides, and seeds, and then using all of this data, they will predict whether or not using this variety of seeds or pesticides will provide good resistance to the plants. However, our approach is based only on the data that we collect and give strategic forecasts that guarantee profit to farmers. Another use case scenario is for the farmer to submit samples to specialists and then wait for feedback. Again, this method is more expensive, time consuming, and prone to errors. Furthermore, there are now available technological platforms that provide equivalent services, but their drawbacks outweigh their advantages. They are compute-intensive, which is inconvenient for the rural farmer, they are not specialized in grape plants, which makes them prone to errors, and they demand exorbitant membership fees. In another scenario, this model can predict the yield with 0% redundancy if there is any devastation caused by locusts (like we have seen in India over the past few days) and how the plant yield may be altered by millions of locusts (swarms).

## 7. CONCLUSION

The project's verification and testing aspects are carried out using some of the evaluation metrics accuracy, loss, precision, and recall - we are glad to announce that our neural network model has been assessed with 97.36 percent accuracy. We used test data to determine the best verification to achieve this milestone, indicating that our perfectly preprocessed dataset was valuable for testing/verification aspects. Because we want to know if adjusting the image pixel ratio will provide important validation to our model or not, we'll need some time to put this in place. Fine parameter tweaking will be done in order to make our model completely error-free, and we are still working on the model's pipeline network.

## REFERENCES

[1] Dhaygude, S. B., & Kumbhar, N. P. (2013). Agricultu ral plant leaf disease detection using image processing. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering 2 (1), 599 602.

[2] Patil, J. K., & Kumar, R. (2011). Advances in image processing for detection of plant diseases. Journal of Advanced Bioinformati cs Applications and Research 2 ( 2), 135 141.

[3] Mainkar, P. M., Gho rpade, S., & Adawadkar, M. (2015). Plant leaf disease detection and classification using image processing techniques. International Journal of Innovative and Emerging Research in Engin eering 2 (4), 139 144.

[4] Gavhale, K. R., & Gawande, U. (2014). An overview of the research on plant leaves disease detection using image processing techniques. IOSR Journal of Computer Engineering (IOSR JCE) 16 (1), 10 16.

[5] Ji, M., Zhang, L., & Wu, Q. (2019). Automatic grape leaf diseases identification via United Model based on multiple convolutional neural networks. Information Processing in Agriculture

[6] Akila, M., & Deepan, P. (2018). Detection and Classification of Plant Leaf Diseases by using Deep Learning Algorithm.

[7] Ashqar, B. A., & Abu Naser, S. S. (2018). Image based tomato leaves diseases detection using deep learning.

[8] Hanson, A. M. G. J., Joel, M. G., Joy, A., & Francis, J. (2017). Plant leaf disease detection using deep learning and convolutional neural network. International Journal of Engineering Science 5324

[9] Rathod, A. N., Tanawal, B., & Shah, V. (2013). Image processing techniques for detection of leaf disease. International Journal of Advanced Research in Computer Science and Software Engineering 3

[10] (Sannakki, S. S., Rajpurohit, V. S., Nargund, V. B., & Kulkarni, P. (2013, July). Diagnosis and classification of grape leaf diseases using neural networks. In 2013 Fourth Internation al Conference on Computing, Communications and Networking Technologies (ICCCNT) (pp. 1 5). IEEE.

[11] Ferentinos, K. P. (Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture 145 311 318.

[12] Gavhale, K. R., Gawande, U., & Hajari, K. O. (2014, April). Unhealthy region of citrus leaf detection using image processing techniques. In Internatio nal Conference for Convergence for Technology 2014 (pp. 1 6). IEEE.

[13] Huang, De-shuang. "Radial basis probabilistic neural networks: Model and application." International Journal of Pattern Recognition and Artificial Intelligence 13.07 (1999): 1083-1101.

[14] Liu, B., Zhang, Y., He, D., & Li, Y. (2018). Identification of apple leaf diseases based on deep convolutional neural networks. Symmetry, 10(1), 11.

[15] Gulhane, V. A., & Gurjar, A. A. (2011). Detection of diseases on cotton leaves and its possible diagnosis. International Journal of Image Processing (IJIP), 5(5), 590-598.

[16] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and electronics in agriculture, 147, 70-90.

[17] Khirade, S. D., & Patil, A. B. (2015, February). Plant disease detection using image processing. In 2015 International conference on computing communication control and automation (pp. 768-771). IEEE.

[18] Sujatha R*, Y Sravan Kumar and Garine Uma Akhil. Leaf disease detection using image processing. Journal of Chemical and Pharmaceutical Sciences.

[19] Lu, Y., Yi, S., Zeng, N., Liu, Y., & Zhang, Y. (2017). Identification of rice diseases using deep convolutional neural networks. Neurocomputing, 267, 378-384.

[20] Meunkaewjinda, A., Kumsawat, P., Attakitmongcol, K., & Srikaew, A. (2008, May). Grape leaf disease detection from color imagery using hybrid intelligent system. In 2008 5th international conference on electrical engineering/electronics, computer, telecommunications and information technology (Vol. 1, pp. 513-516). IEEE.

[21] Prasad, S., Peddoju, S. K., & Ghosh, D. (2014, April). Energy efficient mobile vision system for plant leaf disease identification. In 2014 IEEE Wireless Communications and Networking Conference (WCNC) (pp. 3314-3319). IEEE.

[22] Revathi, P., & Hemalatha, M. (2012, December). Classification of cotton leaf spot diseases using image processing edge detection techniques. In 2012 International Conference on Emerging Trends in Science, Engineering and Technology (INCOSET) (pp. 169-173). IEEE.

[23] Rothe, P. R., & Kshirsagar, R. V. (2015, January). Cotton leaf disease identification using pattern recognition techniques. In 2015 International Conference on Pervasive Computing (ICPC) (pp. 1-6). IEEE.

[24] Singh, V., & Misra, A. K. (2017). Detection of plant leaf diseases using image segmentation and soft computing techniques. Information processing in Agriculture, 4(1), 41-49.

[25] Sun, G., Jia, X., & Geng, T. (2018). Plant diseases recognition based on image processing technology. Journal of Electrical and Computer Engineering, 2018.

[26] Patil, S. B., & Bodhe, S. K. (2011). Leaf disease severity measurement using image processing. International Journal of Engineering and Technology, 3(5), 297-301.

[27] Vibhute, A., & Bodhe, S. K. (2012). Applications of image processing in agriculture: a survey. International Journal of Computer Applications, 52(2).

[28] McDonald, T., & Chen, Y. R. (1990). Application of morphological image processing in agriculture. Transactions of the ASAE, 33(4), 1346-1352.

[29] Sabliov, C. M., Boldor, D., Keener, K. M., & Farkas, B. E. (2002). Image processing method to determine surface area and volume of axi-symmetric agricultural products. International Journal of Food Properties, 5(3), 641-653.

[30] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and electronics in agriculture, 147, 70-90.

[31] Tillett, R. D. (1991). Image analysis for agricultural processes: a review of potential opportunities. Journal of agricultural Engineering research, 50, 247-258.

[32] Khirade, S. D., & Patil, A. B. (2015, February). Plant disease detection using image processing. In 2015 International conference on computing communication control and automation (pp. 768-771). IEEE.

[33] Petrellis, N. (2017, May). A smart phone image processing application for plant disease diagnosis. In 2017 6th International Conference on Modern Circuits and Systems Technologies (MOCAST) (pp. 1-4). IEEE.

[34] Sanjana, Y., Sivasamy, A., & Jayanth, S. (2015). Plant disease detection using image processing techniques. International Journal of Innovative Research in Science, Engineering and Technology, 4(6), 295-301.

[35] Barbedo, J. G. A., Koenigkan, L. V., & Santos, T. T. (2016). Identifying multiple plant diseases using digital image processing. Biosystems engineering, 147, 104-116.

[36] DO VALE, F. X. R., FILHO, E. I. F., LIBERATO, J. R., & ZAMBOLIM, L. (2001). Quant-A software to quantify plant disease severity. In International workshop on plant disease epidemiology (Vol. 1, p. 161).

[37] Meunkaewjinda, A., Kumsawat, P., Attakitmongcol, K., & Srikaew, A. (2008, May). Grape leaf disease detection from color imagery using hybrid intelligent system. In 2008 5th international conference on electrical engineering/electronics, computer, telecommunications and information technology (Vol. 1, pp. 513-516). IEEE.

[38] Kakade, N. R., & Ahire, D. D. (2015). Real time grape leaf disease detection. Int J Adv Res Innov Ideas Educ (IJARIIE), 1(04), 1.

[39] Padol, P. B., & Sawant, S. D. (2016, December). Fusion classification technique used to detect downy and Powdery Mildew grape leaf diseases. In 2016 International Conference on Global Trends in Signal Processing, Information Computing and Communication (ICGTSPICC) (pp. 298-301). IEEE.

[40] Patil, J. K., & Kumar, R. (2011). Advances in image processing for detection of plant diseases. Journal of Advanced Bioinformatics Applications and Research, 2(2), 135-141.

[41] Kakade, N. R., & Ahire, D. D. (2015). Real time grape leaf disease detection. Int J Adv Res Innov Ideas Educ (IJARIIE), 1(04), 1.

[42] Hanson, J., Joy, A., & Francis, J. (2016). Survey on image processing based plant leaf disease detection. International Journal of Engineering Science, 2653.

[43] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in plant science, 7, 1419.

[44] Kumar, S., & Kaur, R. (2015). Plant disease detection using image processing-a review. International Journal of Computer Applications, 124(16).

[45] Prakash, B., & Yerpude, A. (2015). A Survey on Plant Leaf Disease Identification. International Journal of Advanced Research in Computer Science and Software Engineering (IJARCSSE), 5(3).

[46] Oo, Y. M., & Htun, N. C. (2018). Plant leaf disease detection and classification using image processing. Int. J. of Res. and Eng, 5(9), 516-523.

[47] Zeiler, M.D.; Fergus, R. Stochastic pooling for regularization of deep convolutional neural networks. arXiv, 2013.

[48] Giusti, A.; Dan, C.C.; Masci, J.; Gambardella, L.M.; Schmidhuber, J. Fast image scanning with deep maxpooling convolutional neural networks. In Proceedings of the 20th IEEE International Conference on Image Processing, Melbourne, Australia, 15–18 September 2013; pp. 4034–4038

[49] Kawasaki, Y.; Uga, H.; Kagiwada, S.; Iyatomi, H. Basic study of automated diagnosis of viral plant diseases using convolutional neural networks. In Proceedings of the 12th International Symposium on Visual Computing, Las Vegas, NV, USA, 12–14 December 2015; pp. 638–645

[50] Sladojevic,S.;Arsenovic,M.;Anderla,A.;Culibrk,D.;Stefanovic,D.Deepneuralnetworksbasedrecognition of plant diseases by leaf image classification. Comput. Intell. Neurosci. 2016, 2016. [CrossRef] [PubMed]