# Phytovision Diagnosis: Identification of Plant Diseases using Deep Learning Techniques

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***Abstract - This paper describes PlantPulse-a web-based application designed for identification of plant diseases using deep learning techniques. Plant diseases greatly reduce global agricultural productivity, which results in losses in yields and economies. So, identifying plant diseases early is of immense importance. However, traditional methods of identifying these plant diseases can be time-consuming. This project aims to leverage deep learning techniques to automate the identification of plant diseases. The study employs a hybrid model combining MobileNetV2 with Resnet50 to classify and identify different plant diseases. The model is trained and validated using a comprehensive dataset of New Plant Diseases dataset images, ensuring robust performance. The User uploads the images of Plant leafs and the results are displayed in upload page itself. Constructed with the Flask framework and MongoDB, this application gives users the ability to register, log in, and view their history of scans, allowing users to upload different format of images. The application also has educational details including - "About", "How It Works," and "Diseases" pages to explain to users the technology behind, its utility and also has details of symptoms and treatment plans for particular diseases. The purpose of this project is to help users to keep their plants healthy.***

***Keywords: Mobilenetv2-Resnet50 hybrid model, New Plant diseases Dataset, Upload page, flask framework, Mongodb, User Profile, user scan history, About page, Home Page, Diseases Page.***

## INTRODUCTION

Plant Disease Classification Web Application is developed to solve the critical issues of the Users to keep their plants healthy from spread of plant diseases as they can lead to the extensive devastation of the other near by plants. The web application uses sophisticated machine learning models for identification and classification of a series of plant diseases efficiently, and this provides the users with a current and beneficial tool to diagnose plant disease situations. Developed on the Flask platform, the application allows users to upload images of plants, and they are subjected to a hybrid deep learning model that integrates the ResNet50 and MobileNetV2 architectures. The hybrid model takes advantage of the strengths of both models: ResNet50 and Mobilenetv2. Resnet50 helps in deep extracting and Mobilenetv2 is a light weight and fast computing model. The Web application has a upload page in which the User uploads different format of images, of plant leafs and the results are displayed in that page itself. The application also contains other features like user authentication, user profile, scan history, treatment plans etc.

The user begins by logging in web page, and uploads the images, the hybrid pretrained model helps in prediction.

After the prediction the user can go to diseases page for treatment plans and also view symptoms for that particular disease. The predictions done by user is stored in user's scan history. The web application contains various navigation links in header containing educational details. The web page has About page -Contains team details, Diseases page-has 38 classes disease symptoms and 3 types of treatment plans, How it works page-has details how to use the application, upload page-for uploading images.

## LITERATURE SURVEY

The papers reviewed investigated different machine learning (ML) and deep learning (DL) models for disease classification in plants, with different methodologies and limitations. For example, [1]one study utilized transfer learning with VGG16 detection that estimated both symmetry and color to classify four classes of grape leaf diseases with an accuracy of 91.66%. The black rot was misclassified, which lowered the F1 score to 0.80 because of class symmetry and color. Similarly, the study mentioned dataset limitations and preprocessing difficulties; background noise and image quality were explained as challenges to accurate classification. However, there was no tested treatment plan or description of symptoms.[2]Another study used mostly image processing and feature extraction techniques instead of deep learning or convolutional neural networks. Random Forest (RF) was used to classify Plant leaf diseases and reported an accuracy of 93%. The study used preprocessing tasks to improve classification, including converting to grayscale for noise removal and Gaussian filtering. The misclassification did occur with RF because agricultural diseases may present similar symptoms with leaves. The study mentions ML but made no suggestions for improvement. The web app web application was used with Flask but was minimally discussed. Similarly, [3]a third study used support vector machine (SVM) classification with polynomial kernel using color and texture features but was repetitive and too vague with the analysis. The accuracy was reported as 95.79% but no explanation of choices made in the study and there were no reference to future management of diseases in practice.[4]A final review paper also summarized different ML and DL methods but was limited in the depth of study discussed as related to CNNs, YOLO, GANs, and hybrid models related to plant diseases.

## EXISTING SYSTEM

The majority of existing disease diagnosis models in plants are highly reliant on deep learning architectures such as Convolutional Neural Networks (CNNs) and approaches such as Principal Component Analysis (PCA), Support Vector Machines (SVM), Singular Value Decomposition (SVD), Scale-Invariant Feature Transform (SIFT), and AlexNet models. These models can make a very accurate inference of world leaf image features such as texture, color texture patterns, vein morphologic patterns, and overall shape that are prime significance in disease diagnosis coupled with distinguishing different plant diseases. A major flaw in currently systems is that they do not incorporate treatment plans or even actionable recommendations towards disease management, and thus they cannot be used in actual farming situations. Furthermore, they are incorrect even in the classification of the image of the actual world. Apart from that, there is no data in the current systems regarding the detailed signs and symptoms of disease, and thus no farm workers and or farmers can have the ability to assess the strength and development of diseases in crops. The absence of symptom analysis again leads to the inability to institute and enact appropriate and timely treatment procedures. The models may work in ideal laboratory conditions, however, they fail in noisy real-world conditions with class imbalance, generalization.

## DRAWBACKS TO EXISTING SYSTEM

1. The current models typically focus on diagnosing a plant disease and simply do not provide a treatment plan or actionable recommendation for disease management. The proposed application not only provides the identification of the disease but also seeks to provide users with how to manage and treat the identified disease.
2. Current existing systems may be missing signs and symptoms of the disease then making it difficult for a farmer to ascertain how severe the diseases are and how they are progressing for the plant. The proposed new application fills this gap in existing systems by providing educational content so that users can learn signs and symptoms of disease, and management strategies for the identified symptoms of diseases.
3. Many of the current existing models perform effectively in laboratory designs with controlled conditions and can be inaccurate in classification in competing noisy real-world conditions and contend with more variables. The proposed application normalizes the conditions to give consistently accurate prediction of processes adding to usability in practical farming scenarios. Also they show low accuracy in real world predictions.
4. Existing systems do not allow for user input or

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ways to log history, what gives to question the overall user experience and learning. The new application increases user engagement by allowing users to create an account and log in to scan and have continuous access to the application.

## PROPOSED SYSTEM METHODOLOGY

Data Collection: The collection encompasses 87K images of plant leaves, classified into both healthy and diseased groups. All images are sourced from Kaggle, and each image label is defined as class-labels based on the name of the disease. Generally, the class labeling process is automated by extracting indicators from the folder names of each image.

Data preprocessing: The dataset is preprocessed using Image Data Generator, where all dataset images are resized to 224×224 pixels and normalized to improve training stability. Data augmentation techniques are applied to enhance the model's generalization ability. The dataset is split into training and validation, ensuring a balanced approach to learning and evaluation.

Model Training: In model training we used two models Resnet50, Hybrid- Resnet50 and Mobilenetv2 the model Resnet50 gives good accuracy scores but fail in identifying plant diseases, if given real world images when compared to hybrid model, also the hybrid model has good accuracy when compared to the Resnet50 alone model

Model Evaluation: Model evaluation is crucial to determine how well the trained model performs on unseen data. Metrics such as accuracy and trainable parameters are calculated to assess the model's effectiveness across different classes of Disease data. Confusion matrices are also used to visualize misclassifications and understand where the model is failing.

Deployment: For deploying the trained model we used Flask application which is used to connect the frontend and backend parts we also used mongoDb to store the user's details and their scan history all the routes for this are applied in app.py file to make it work. The user uploads the image after login and the results are displayed and after that he can view the treatment plans accordingly in the diseases page for that particular disease.

The project design facilitates a user-friendly experience, allowing users to create accounts, upload plant images, and receive diagnoses from a pre-trained ResNet50-MobilenetV2-LSTM model. Users are provided with disease identification, symptom descriptions, management protocols, and access to their scan history, promoting engagement and effective plant care.

## PROPOSED SYSTEM ARCHITECTURE

The project's architecture is structured to facilitate appropriate interactions between users, the application, and the Deep learning model. Using Flask, the front-end creates an intuitive method for users to upload images, receive predictions, and learn about plant diseases, where users can upload an image of their plant, the image is processed before being sent to be run through the back-end application. The back-end application uses a pre-trained ResNet50- MobileNetV2-LSTM model to retrieve data, analyze uploaded pictures for any observed plant diseases, and identify potential diseases regarding identified features such as texture of the leaves and color patterns.

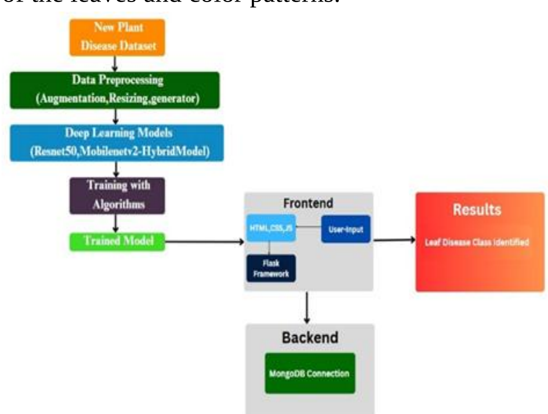


Fig:[1]:Proposed system Architecture

The database, MongoDB, is utilized for the storage of user information, scanning history, and any other useful documents associated with the ability to create user accounts for user tracking of their plant health over time. The front-end and back-end applications will communicate with each other via an API that can handle an image processing request and return the previous model predicting result. In addition, the architecture has a provision for the user to receive recommendations and education for managing the identified plant disease in order to assess and maintain plants health. In summary, this architectural framework is developed to assist in a user friendly framework to essential plant disease identification and manageable recommendations.

## PROPOSED SYSTEM ALGORITHMS

ResNet50 (Residual Network 50 layers):It is a deep learning model that solves difficulties with training very deep neural networks. The main idea behind ResNet50 is its hypothesis of residual connections which allows the model to learn residual mappings by introducing shortcut connections that skip one or more layers. This architecture helps to improve the flow of gradients during backpropagation, which helps to solve the vanishing gradient problem. The ResNet50 architecture has achieved a very high degree of accuracy on image classification tasks including on the ImageNet dataset. For the hybrid model for the Plant Disease Classification Web Application, the ResNet50 model is embedded in the model in service of its powerful capability as a feature extractor for more precise disease detection.

MobileNetV2: It is an efficient deep learning architecture that is designed for image classification. It uses depth wise separable convolutions to reduce compute cost while still maintaining accuracy. This makes MobileNetV2 particularly useful for real-time applications, including the plant disease classification use case we implemented in the Plant Disease Classification Web Application.

Hybrid Model: The hybrid model combines ResNet50 and MobileNetV2, utilizing the benefits of both models, and improves image classification performance, especially in distinguishing between different plant diseases. ResNet50 is strong in deep feature extraction with its residual connections allowing it to learn complicated features well. This is essential for accurately identifying specific plant disease. MobileNetV2 is purposely designed to have a light-weight architecture, using depth wise separable convolutions in efforts to minimize computational burden while maintaining accuracy. This means MobileNetV2 is easier to use in mobile and edge devices for on-demand or real-time prediction. The combination of these two models means the team will provide the balance of cost-efficiency and accuracy, so that the Plant Disease Classification Web Application is capable of providing an accurate result in a reasonable amount of time, and quickly enough for users who need urgency and immediate feedback on the health of their plant.

## DATASET DESCRIPTION

The New Plant Diseases Dataset contains more than 87,000 RGB images and has been generated to facilitate the development of machine learning models to detect and classify plant diseases. There are 38 total classes of healthy and diseased crop leaves. The dataset presents the following benefits: Large Dataset, has 38 classes in it, Dataset Organization-The dataset is organized into two sections that will work best for machine learning model efforts. Training dataset: 80% of the dataset elements are included in the training portion and serve as a helpful structure when training machine learning models on the dataset. Validation dataset: This is the other 20% of the dataset, which anticipates an evaluation of a meaningful model.

## BENEFITS OF PROPOSED SYSTEM

The Plant Disease Identification Web Application offers many advantages. First, the plant disease diagnosis is quick and precise so that users are allowed to understand any plant health issues and intervene timely to avoid plant loss. Second, the interface is easy to use so that users of all skill levels can browse images and obtain results seamlessly. Third, our application allows for scan history that enables users to have access to their plant health scans at any time which can lead to more informed decisions. Lastly, the additional content offered in the application can help users to establish management goals based on plant diseases and management options. Overall, this is an excellent and useful project with the potential to improve the plant diagnosis and promote sustainable plant health.

## RESULTS

Results from our experimental evaluation show that the model performs well with Training accuracy of 98% and a validaton accuracy of 96%. It performs well in analyzing plant leaf images and displaying results as accurate as possible (works for real time images also).

The User uploads the image of plant leaf and on clicking Upload and Analyze the prediction results are displayed below the Upload and Analyze buttons as Analysis results. The user can visit the diseases page for treatment plans and other info. Also the user scan history is stored in user profile.

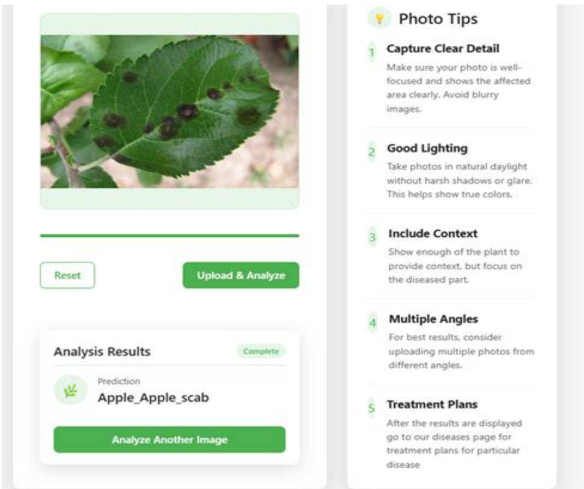


Fig:[2]Results Page

WEB APPLICATION INTERFACE IMAGES


Fig:[3]Home page

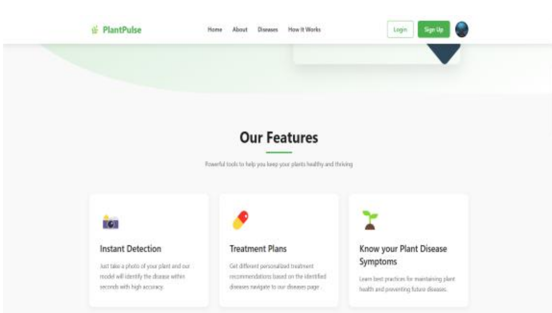


Fig:[4]Home Page on scrolling

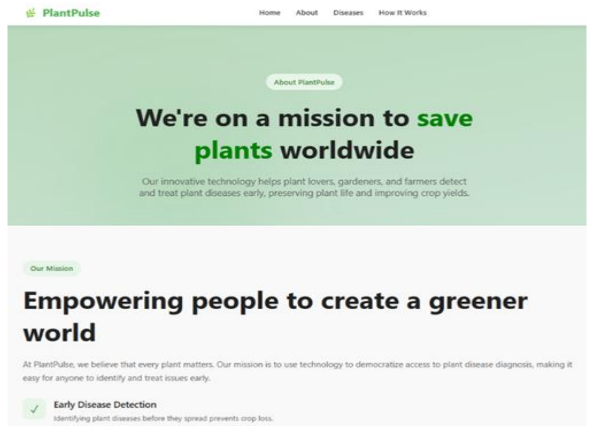


Fig:[5]About Page

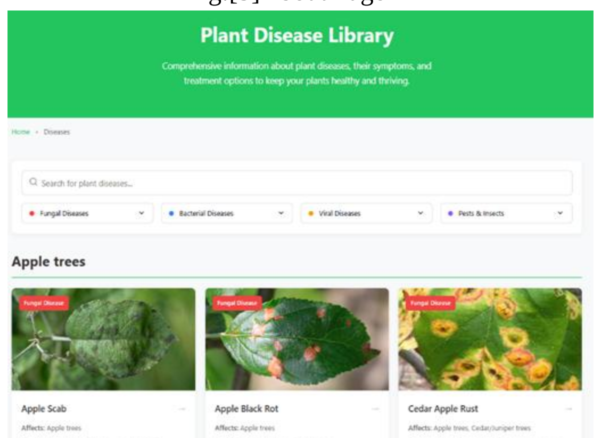


Fig:[6]Diseases Page

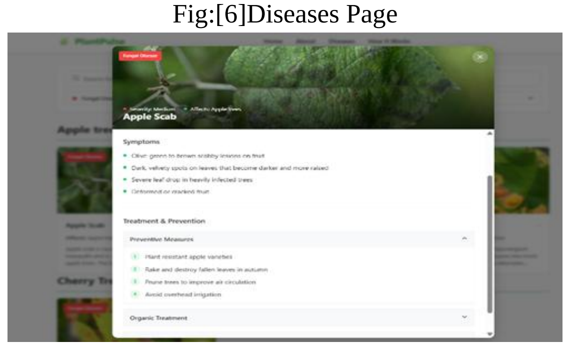


Fig:[7]Treatment Plans, symptoms data in diseases Page


Fig:[8]Howit works page

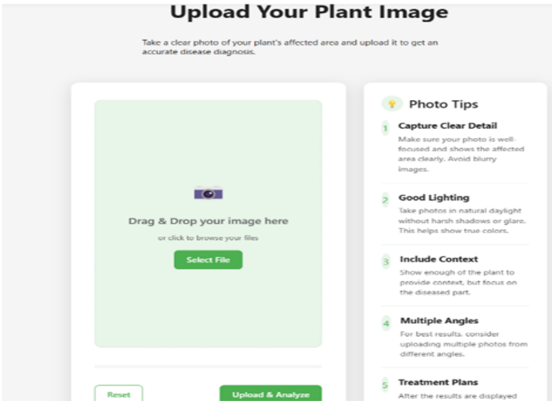

Fig:[9]Upload page

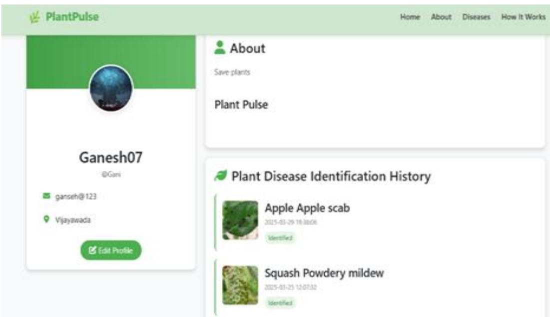

Fig:[10 ]User Profile page

## CONCLUSION

In conclusion, the Plant Disease Classification Web Application represents an important advancement in analyzing the plant leafs for diseases. This technology can be used to keep the plants healthy and identify and manage plant diseases. The project leverages a hybrid model between ResNet50 and MobileNetV2 and provides farmers with accurate and efficacious predictions, thus allowing farmers to make informed decisions about their crop. The usability of the Web Application, including functions such as scan history and more details about the disease, provides flow to the user experience. The Plant Disease Classification Web Application is not limited to simply showcasing the benefits of applying machine learning technologies in agriculture, it also underscores the importance of rapidly and accurately identifying and managing plant disease in order to facilitate and encourage sustainable agriculture and food security.

## FUTURE SCOPE

Advancements in Model Accuracy and Efficiency, You can use advanced combination of some hybrid Deep learning models to achieve good accuracy that perform well for real world predictions. Larger and Diverse Dataset, Future advancements will enable the inclusion of vast and diverse plant species from different geographical regions. So, vast datasets can be used for training which improves the real time classification much more. By incorporating multilingual and region-specific datasets, the system can help users across the globe access precise plant disease information, supporting treatment plans and suggestions based on the disease.
Including Chat feature, The proposed chat feature helps the users to engage in real-time consultations with the trained bot and ask questions related to their plant health or any other questions related to plants and receive personalized advice, and gain insights into effective management strategies. It enhances user support and improves overall user experience and promotes better plant care practices.

## REFERENCES

[1] 1.Bhavya Jain, Sasikumar Periyasamy (2021)," Grapes Disease Detection Using Transfer Learning"-A Review"
[2] Pranesh Kulkarni, Atharva Karwande, Tejas Kolhe, Soham Kamble, Akshay Joshi, Medha Wyawahare (2021),"Plant Disease Detection Using Image Processing and Machine Learning"
[3] Nisar Ahmad, Hafiz Muhammad Shahzad Asif, Gulshan Saleem, Muhammad Usman Younus, Sadia Anwar, Muhammad Rizwan Anjum (2021),"Leaf Image-based Plant Disease Identification using Color and Texture Features"DOI:10.1007/s11277-021-09054-2
[4] Wubetu Barud Demilie(2024),"PlantDisease Detection and Classification Techniques: A Comparative Study of the Performances", DOI: 10.1186/s40537-023-00863-9
[5] Demilie, W.B(2024). Plant disease detection and classification techniques: a comparative study of the performances. J Big Data 11, 5.
[6] Natarajan, S., Chakrabarti, P. & Margala(2024), M. Robust diagnosis and meta visualizations of plant diseases through deep neural architecture with explainable-AI. *Sci-Rep* 14,13695 https://doi.org/10.1038/s41598-024-64601-8
[7] Singh, Davinder & Jain, Naman & Jain, Pranjali

& Kayal, Pratik & Kumawat, Sudhakar & Batra, Nipun. (2020). PlantDoc: A Dataset for Visual Plant Disease Detection. 249-253. 10.1145/3371158.3371196.

[8] Farooq, Shoaib & Arif, Tabir & Riaz, Shamyla. (2023). Detection of Late Blight Disease in Tomato Leaf-Using-Image-Processing-Techniques. 10.48550/arXiv.2306.06080.

[9] Sebastian, A., Fathima, A.A., Pragna, R., MadhanKumar, S., Kannan, G.Y., Murali, V. (2024). In: Bansal, J.C., Borah, S., Hussain, S., Salhi, S. (eds) Computing and Machine Learning. CML 2024.

[10] V. K. Vishnoi, K. Kumar, B. Kumar, S. Mohan and A. A. Khan (2023), "Detection of Apple Plant Diseases Using Leaf Images Through Convolutional Neural Network," in IEEE Access, vol. 11, pp. 6594-6609, 2023.

[11] X. Liu, W. Min, S. Mei, L. Wang and S. Jiang, (2021)."Plant Disease Recognition: A Large-Scale Benchmark Dataset and a Visual Region and Loss Reweighting Approach," in IEEE Transactions on Image Processing, vol. 30, pp. 2003-2015.

[12] Mohanty SP, Hughes DP and Salathé M (2016) Using Deep Learning for Image-Based Plant Disease Detection. *Front.Plant-Sci.* 7:1419.doi: 10.3389/fpls.2016.01419

[13] Jianping Yao, Son N. Tran, Saurabh Garg, and Samantha Sawyer-(2024). Deep Learning for Plant Identification and Disease Classification from Leaf Images: Multi-prediction Approaches. ACM Comput.Surv. 56, 6, Article 153 (June 2024), 37 pages.

[14] Mustofa, Sumaya & Munna, Md & Emon, Yousuf & Rabbany, Golam & Ahad, Md. (2023). A comprehensive review on Plant Leaf Disease detection using Deep learning. 10.48550/arXiv.2308.14087.

[15] Bhuiyan, M. A. B., Abdullah, H. M., Arman, S. E., Rahman, S. S., & Al Mahmud, K. (2023). BananaSqueezeNet: A very fast, lightweight convolutional neural network for the diagnosis of three prominent banana leaf diseases. Smart Agricultural Technology, 4, 100214, https://doi.org/10.1016/j.atech.2023.100214

[16] Sethy, P. K., & Behera, S. K. (2020). Rice leaf disease identification using hierarchical convolutional neural network. Indonesian Journal of Electrical Engineering and Computer-Science,20(1),141–147. http://doi. org/10.11591/ijeecs.v20.i1.pp141-147

[17] Amara, J., Bouaziz, B., & Algergawy, A. (2017). A Deep Learning-based Approach for Banana Leaf Diseases Classification. BTW (Workshops), 2017, 79–88.https://www. researchgate.net/publication/316941074_A_Deep_Learningbased_Approach_for_Banana_Leaf_Diseases_Classification

[18] Picon, A., Alvarez-Gila, A., Seitz, M., Ortiz-Barredo, A., & Echazarra, J. (2019). Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild. Computers and Electronics in Agriculture, 161, 280–290. https://doi.org/10.1016/j.compag.2018.03.032

[19] Rangarajan, A. K., Purushothaman, R., & Ramesh, A. (2018). Tomato crop disease classification using pre-trained deep learning algorithm. Procedia Computer Science, 133, 1040–1047. [https://doi.org/10.1016/j.procs.2018.07.070]

[20] Lawrence C. Ngugi, Moataz Abelwahab, Mohammed Abo-Zahhad, Recent advances in image processing techniques for automated leaf pest and disease recognition – A review, Information Processing in Agriculture, Volume 8, Issue 1, 2021, Pages 27-51, ISSN 2214-3173, https://doi.org/10.1016/j.inpa.2020.04.004.