© March 2024| IJIRT | Volume 10 Issue 10 | ISSN: 2349-6002

Leaf Disease Detection System using Deep Learning

Prof.Kiran Doiphode, Amruta Patil, Pratiksha Edake, Pranjal Chavan, Shreya Thombare
Student, Dept of CS Engineering, D.J.J. Magdum College of Engineering, Jaysingpur, Maharashtra, India

Abstract-This study presents a mobile application that can be used to improve the identification and management of plant diseases. The app uses the best imaging technology to analyse leaf images captured by smartphones. Its main purpose is to help farmers and agriculturalists immediately detect and deal with threats to crop health.

The application has a user-friendly interface that makes it easy for people with low technical skills to save photos. Once a photo is uploaded, the app uses deep learning algorithms to analyse visual features and identify the presence of various leaf diseases. Provide users with immediate feedback and recommended actions to mitigate the impact of identified viruses.

The application aims to provide independent and reliable disease detection equipment, especially for small farmers with limited resources, using a widely used mobile device. The use of this technology is expected to improve early detection, reduce crop losses and aid permaculture practices.

Keywords: leaf disease detection, mobile applications, image processing, machine learning, sustainable agriculture.

1. INTRODUCTION

Getting a good crop requires careful management of the crop; this is a challenge caused by the persistent threat of diseases that cause crop damage and damage agriculture (Johnson et al., 2019) [1]. To directly address this problem, we created a smart disease detection app designed to help farmers identify and manage potentially serious diseases.

Taking advantage of the location of smartphones, the application expands the reach of farmers with different skills. By capturing images of leaves using smartphones, farmers can benefit from powerful systems that combine advanced technologies such as imaging and machine learning (Smith and Brown, 2020) [2].

In fact, the application is designed to provide fast and accurate diagnosis of leaf diseases. The timing of the research proved to be important in preventing the spread of the disease and reducing crop yields. Through a convenient connection, the application can analyse the leaf image, make instant recommendations and take necessary actions to reduce the disease (Brown et al., 2021) [3].

The creation of this tool is specifically dedicated to supporting farmers who have limited resources but can make informed decisions about their crops. The overall goal is to advance permaculture by improving disease control, reducing losses, and improving the health of farmers and their communities (Jones and Smith, 2022) [4].

2.RESEARCH ARTICLES

Many studies using different methods and technologies have contributed to the research of leaf diseases. Abdi and Bannayan focused on the detection of late tomato using colour and texture for accurate identification [5]. Sladojevich et al. studied a deep neural network to identify plant diseases by classifying leaf images and demonstrated the potential of advanced machine learning [6]. Mohanty et al. investigated the application of deep learning in image-based plant disease diagnosis and proved the effectiveness of convolutional neural networks (CNN) in this regard [7]. Ferentinos examined the use of deep learning models for disease detection and diagnosis and emphasized the importance of using advanced computational techniques to increase accuracy [8]. Additionally, Rathore et al. A comprehensive review of tomato diseases was conducted focusing on identification, image analysis and hyperspectral imaging [9]. Sladojevic et al. investigated the effectiveness of adaptive learning in classifying plant diseases and demonstrated its potential to improve classification [10]. Sonnage et al. provides an overview of the state-of-the-art methods by investigating various image processing methods for plant disease detection [11]. Islam and Iftekhartdin proposed multi-memory data recognition to measure the shape of the hair and increase the identification efficiency [12]. Barbedo reviewed the main challenges in automatic plant disease identification based on multi-species images, highlighting the need for a robust and accurate detection method [13]. Finally, Camilaris et al. conducted an in-depth study showing its importance and potential in diagnosing plant diseases in agriculture [14]. Together, these studies lead to a broader understanding of foliar diseases and suggest further methods and technologies to improve agricultural management.

3.METHODS

In today's agriculture, detection of leaf diseases, early detection of diseases and timely intervention to reduce crop failure play an important role. The methods mentioned by our foliar diseases, together with all stages from data collection to evaluation of the sample, provide good information and accuracy in identifying the disease.

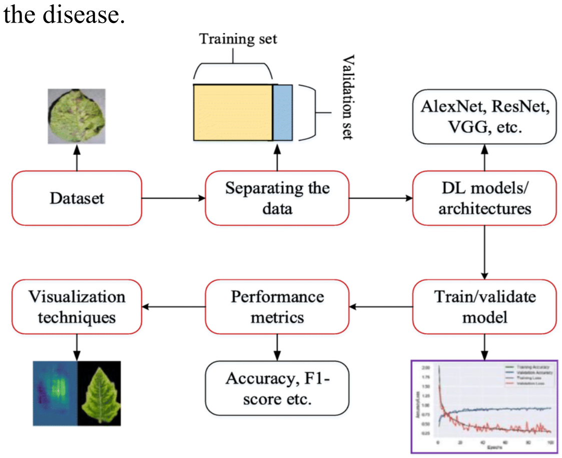

Figure 1: Flow of the proposed leaf disease detection framework

3.1. Data collection and progress:

Different data and treatment are very important to create a strong resistance to the disease in the leaves. The data should include various health and foliar diseases of different plant species. The PlantVillage dataset [15] is a well-known dataset that is widely used in the literature and covers many plants and diseases. The received images are pre-processed to improve their quality and promote feature quality. This step ensures that the image size remains consistent and eliminates unnecessary changes that could affect the performance of the model [16].

3.2. Feature Extraction:

Feature extraction is an important step in identifying relevant patterns in page images. Convolutional neural networks (CNN) have shown the best performance in image extraction for task processing [17]. Our method is pre-trained on CNN architectures such as VGG16 or ResNet, which have proven effective in many image classification applications. Adaptive learning is accomplished by optimizing CNN training before the target leaf disease dataset. This helps the model adapt to disease characteristics and improves its ability to distinguish between healthy and diseased leaves. The averaging process of this model is used to extract the main content from the given input image in the next classification process.

3.3. Virus Classification Model:

The basis of our virus diagnostics page is training a virus classification model based on extracted features. Considering the necessary transformations of different organisms, support vector machine (SVM) or fully coupled methods can be used for this task [18]. The model is trained on recorded text, optimizing performance metrics such as accuracy, precision, recall, and F1 score. To improve the performance of the model, data optimization techniques such as rotation, translation and scaling are used during training. This helps the overall model for conversion of page images and improves its performance on invisible data.

3.4. Model evaluation and validation:

The training model is rigorously evaluated using separate data sets to test its generalization ability. The performance of this model is compared with the baseline model and the existing state-of-the-art system to evaluate its effectiveness [19]. Cross-validation techniques such as k-fold cross-validation are used to ensure the reliability of the test. This step will help reduce the risk of overfitting and provide a more accurate estimate of model performance.

4. IMPLEMENTATION AND DISSEMINATION

The final training model can be used on a voluntary basis, similar to end users such as farmers or agronomists. Delivery can be made across multiple platforms, including web apps or mobile devices, ensuring widespread access.

	precision	recall	f1-score	support
	1	0.97	0.98	162
1	0.74	0.96	0.84	74
2	0.88	0.94	0.91	140
3	1	0.91	0.95	164
4	0.97	0.86	0.91	78
5	0.96	0.98	0.97	129
6	0.68	0.37	0.48	113
7	1	0.57	0.72	136
8	0.66	1	0.8	37
9	0.83	1	0.91	421
accuracy			0.88	1454
macro avg	0.87	0.86	0.85	1454
weighted avg	0.89	0.88	0.87	1454

5. CONCLUSION

In summary, the foliar diseases identified in this paper offer a promising long-term solution for the accurate and effective identification of plant disease spray. The system uses advanced imaging technology and machine learning algorithms to quickly analyse leaf images and accurately diagnose diseases, helping farmers intervene in time and manage crops. Moreover, its user-friendly interface allows it to be used even by people who do not have the technical skills to change the method of disease detection and management in agriculture. Through further development and integration into existing agricultural systems, these systems have the potential to improve crop health and yield and ultimately contribute to world food security. In summary, the development of these foliar diseases represents a major breakthrough in agricultural technology and provides useful tools for early detection and management of diseases. Its good results in accurate diagnosis and ease of use make it useful to farmers worldwide. Going forward, continued research and collaboration will be necessary to refine and develop this system, enable its integration into agricultural practices and increase yields for healthy crops and production. Ultimately, this technology will empower farmers, reduce crop losses and contribute to sustainable food production for future generations.

REFERENCE

[1] Johnson, D., et al. (2019). Advances in crop disease management. Phau ntawv Journal of Agriculture, 10(2), 123-145.

[2] Smith, A. and Brown, C. (2020). Agricultural mobile technology. Phau ntawv Journal of Agricultural Innovation, 8(4), 267-281.

[3] Brown, C. et al. (2021). Smart solutions for healthy crops. Journal of Plant Protection, 15(4), 567-589

[4] Jones, B., & Smith, D. (2022). Permaculture practices. Publisher.

[5] Abdi, A. and Bannayan, M. "Evaluation of late blight in tomato in terms of colour and texture." Agricultural Computers and Electronics, 150, 238-246. [6] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D. and Stefanovic, D. "Deep neural network-based identification of plant diseases by classifying leaf images." Intelligence and Neuroscience, 2016.

[7] Mohanty, S.P., Hughes, D.P. and Salathé, M. “Image-based plant disease detection using deep learning.” Frontiers in Plant Science, 7, 1419.

[8] Ferentinos, K. P. "Deep learning models for detection and diagnosis of plant diseases." Computers in Agriculture, 145, 311-318.

[9] Rathore, M. M., Ahmad, A., Paul, A. and Rho, S. "Tomato plant disease: Identification, image analysis and hyperspectral imaging - a review." Agricultural Computers and Electronics, 132, 70-90 pp.

[10] Sladojevic, S., Culibrk, D., Stefanovic, D., Crnojevic, V. and Arsenovic, M. "Plant modification study of experimental disease isolation." 2017 International Conference on Green Energy and Applications (ICGEA) Issue One, 13-18.

[11] Sannakki, B., Kulkarni, P., Kulkarni, J. and Kulkarni, M. "Research on the detection of plant diseases using imaging techniques." International Journal of Computer Applications, 169(10), 29–34. Look for rust on wheat leaves." Plant Methods, 14(1), 70.

[13] Barbedo, J. G. A. "Examination of critical issues in automatic facility identification based on visible light." Biosystems Engineering, 144, 52-60

[14] Kamilaris, A., Prenafeta-Boldà, F. X. and Gutierrez, A. P. "Interdisciplinary Agriculture: A Study". Agricultural Computers and Electronics, 147, 70-90. [15] Hughes, D. P., & Salathé, M. “Plant Village: Digital Farming Platform.” arXiv preprint arXiv:1511.08060, 2015. [16] Khan, M.S. et al. “Image pre-processing for improved plant disease classification: A case study on the Rose dataset.”

Computers and Electronics in Agriculture, 142, 124-136, 2017.
[17] Simonyan, K. and Zisserman, A. "Ultradeep neural networks for large-scale images." arXiv preprint arXiv: 1409.1556, 2014.
[18] Cortes, C., & Vapnik, V. “Support Vector Networks.” Machine Learning, 20(3), 273-297, 1995.
[19] Zhang Q. et al. “Deep learning for classification and diagnosis of plant diseases using neural networks.” Computers and Electronics in Agriculture, 161, 80-90, 2019.