International Journal of Interdisciplinary Innovative Research & Development (IJIIRD)
ISSN: 2456-236X
Vol. 09 Issue 01 | 2025

Plant Disease Prediction Systems: A Comprehensive Review

Manjiri U. Karande[1], Mandar K. Deshmukh[2]
[1]Assistant Professor, Department of Computer Science & Engineering,
VBKCOE, Malkapur
[2]Assistant Professor, Department of Computer Science & Engineering, COET, Akola

ABSTRACT

The timely and accurate prediction of plant diseases is essential for enhancing food security and agricultural productivity. Traditional methods of disease detection are labor-intensive and subjective, prompting the need for more advanced systems. This review examines the current state-of-the-art in plant disease prediction, highlighting critical aspects such as image acquisition, preprocessing, feature extraction, and the application of machine learning algorithms. Various techniques, including Convolutional Neural Networks (CNNs) for feature extraction and classification, are discussed alongside the integration of Internet of Things (IoT) technologies for real-time monitoring and data collection. The importance of robust datasets and data augmentation methods, such as Generative Adversarial Networks (GANs), is underscored to enhance model performance. Despite significant advancements, challenges persist, including the variability of disease symptoms and the need for efficient algorithms. Future directions emphasize the development of hybrid approaches, improved training datasets, and user-friendly interfaces to facilitate widespread adoption. The ongoing evolution of plant disease prediction systems, driven by technological advancements, holds promise for optimizing agricultural practices and addressing global food demands sustainably.

Keywords: Plant Diseases, CNN, IoT, GAN.

1. INTRODUCTION

The accurate and timely prediction of plant diseases is crucial for ensuring food security and optimizing agricultural productivity. Traditional methods of plant disease detection rely heavily on visual inspection by trained experts, a process that is time-consuming, labor-intensive, subjective, and prone to human error [1]. The advent of advanced technologies, particularly in the fields of image processing, machine learning, and the Internet of Things (IoT), has revolutionized plant disease detection and prediction. This review explores the current state-of-the-art in plant disease prediction systems, examining various techniques, challenges, and future research directions.

1.1 Image Acquisition and Preprocessing

The foundation of any effective plant disease prediction system lies in high-quality image acquisition. Various methods are employed for capturing images of plant leaves, including handheld cameras, drones equipped with high-resolution cameras [2], and specialized sensors integrated with IoT networks [3]. The quality of acquired images significantly impacts the accuracy of subsequent analysis. Factors such as lighting conditions, background noise, and image resolution all play a crucial role [4]. Therefore, robust preprocessing techniques are necessary to enhance image quality and prepare the data for machine learning algorithms. These techniques typically include noise reduction, image enhancement, and segmentation [5]. Image segmentation, the process of partitioning an image into meaningful regions, is particularly important for isolating diseased areas from healthy tissue [6]. Different segmentation methods, such as thresholding [7] and k-means clustering [8], are employed depending on the specific characteristics of the images and the desired level of detail. The selection of appropriate preprocessing techniques is crucial for optimizing the performance of the prediction system [4].

1.2 Feature Extraction and Selection

Once the images are preprocessed, relevant features need to be extracted to represent the data in a format suitable for machine learning algorithms. Feature extraction aims to capture the essential characteristics of the images that are indicative of plant diseases. Traditional methods rely on handcrafted features, such as color, texture, and shape descriptors [1]. However, these methods often require significant domain expertise and may not capture the complex patterns present in plant disease images. Deep learning approaches, particularly Convolutional Neural Networks (CNNs), have revolutionized feature extraction by automatically learning relevant features directly from the raw image data [9]. CNNs excel at capturing spatial hierarchies of features, making them particularly well-suited for image analysis tasks [10]. The choice of CNN architecture (e.g., AlexNet, VGG16, ResNet, Inception, DenseNet) depends on factors such as dataset size, computational resources, and the desired level of accuracy [11], [12]. Transfer learning, the process of leveraging pre-trained models on large datasets (like ImageNet) for feature extraction, is frequently employed to enhance performance, especially when dealing with limited datasets typical in agricultural contexts [12], [9]. Feature selection techniques, such as Particle Swarm Optimization (PSO) [13] and the exponential spider monkey optimization (ESMO) [14], are used to reduce the dimensionality of the feature space, improving computational efficiency and mitigating the risk of overfitting [14]. The optimal feature extraction and selection methods vary depending on the specific plant species, disease, and imaging conditions [4].

2. CLASSIFICATION AND PREDICTION ALGORITHMS

A wide range of machine learning algorithms are employed for classifying plant diseases based on the extracted features. These algorithms can be broadly categorized into traditional methods and deep learning approaches. Traditional methods include Support Vector Machines (SVMs) [15], [16], K-Nearest Neighbors (K-NN) [15], [8], and Probabilistic Neural Networks (PNNs) [17]. These methods have been successfully applied to plant disease classification, but their performance may be limited compared to deep learning approaches. Deep learning algorithms, particularly CNNs, have shown remarkable success in plant disease classification [4], [18]. CNNs have demonstrated superior accuracy compared to traditional methods in various studies, Ensemble methods, which combine multiple classifiers to improve prediction accuracy, have also been explored [18]. For example, the PlantDiseaseNet model uses an ensemble of CNNs for enhanced performance [18]. Other techniques like Radial Basis Function Neural Networks (RBFNNs) [19], optimized with algorithms like Bacterial Foraging Optimization (BFO) [19] or Jaya algorithm [20], further enhance the accuracy and speed of disease identification. The choice of classification algorithm depends on the dataset size, computational resources, and the desired level of accuracy [21]. Furthermore, hybrid approaches that combine traditional machine learning techniques with deep learning methods are gaining popularity, aiming to leverage the strengths of both approaches [22]. For instance, combining CNNs for feature extraction with SVMs for classification has shown promising results [22].

2.1 IoT Integration and Real-Time Applications

The integration of IoT technologies provides significant opportunities for enhancing the capabilities of plant disease prediction systems. IoT devices, including sensors, actuators, and wireless communication networks, enable real-time data acquisition and automated decision-making [3]. Sensors can monitor various environmental parameters, such as temperature, humidity, and soil moisture, which are crucial for predicting disease outbreaks [8]. This data, combined with images captured by cameras, can be used to develop more accurate and reliable prediction models [10]. Mobile applications, coupled with the IoT, facilitate the widespread deployment of plant disease prediction systems, providing farmers with timely alerts and recommendations [11], [23]. The Plant Village Nuru application, for example, leverages machine learning for diagnosing plant health issues through image analysis and is deployed in developing countries via crowd-sensing frameworks [23]. The integration of IoT and machine learning enables the development of smart farming systems that can optimize resource utilization and minimize crop losses [24], [25]. Real-time monitoring and early detection of diseases allow for timely interventions, such as targeted pesticide application or other management strategies [26], leading to improved crop yields and reduced environmental impact [26].

2.2 Datasets and Data Augmentation

The performance of plant disease prediction systems is highly dependent on the quality and quantity of training data. Large, diverse datasets are crucial for training effective machine learning models, particularly deep learning models [4]. However, acquiring and annotating such datasets can be challenging and expensive [27]. The creation of comprehensive plant disease image databases, such as the PDDB and its expanded version XDB [27], is essential for advancing the field. Data augmentation techniques, which artificially increase the size and diversity of the training dataset, play a vital role in enhancing model performance [28], [29]. These techniques can involve transformations such as rotations, flips, and color adjustments, which help the model generalize better to unseen data [28]. Generative Adversarial Networks (GANs) are emerging as a powerful tool for data augmentation, capable of generating realistic synthetic images of plant diseases [30], [31]. The use of GANs can significantly improve the performance of plant disease prediction systems, particularly when dealing with limited or imbalanced datasets [30]. The availability of publicly accessible datasets and the development of robust data augmentation techniques are critical for fostering further research and development in this field [18].

3. CHALLENGES AND FUTURE DIRECTIONS

Despite significant advancements, several challenges remain in developing robust and widely applicable plant disease prediction systems. One major challenge is the variability of disease symptoms, which can be influenced by various factors such as environmental conditions, plant genetics, and the pathogen strain [32]. This variability can make it difficult to develop models that generalize well across different conditions [32]. Another challenge is the need for robust feature extraction techniques that can effectively capture the complex patterns present in plant disease images [4]. Developing methods for handling noisy images and imbalanced datasets remains an active area of research [32]. Furthermore, the deployment of plant disease prediction systems in real-world agricultural settings presents logistical and economic challenges [32]. Future research should focus on developing more robust and efficient algorithms, improving the quality and diversity of training datasets, and exploring novel approaches for integrating sensor data with image data [10]. The development of user-friendly interfaces and the integration of decision support systems for farmers are crucial for ensuring the widespread adoption of these technologies [21]. Research into methods for early disease detection, even before visual symptoms become apparent, is also essential for effective disease management [16]. The exploration of hybrid approaches, combining multiple sensing modalities and machine learning techniques, holds a significant promise for developing more accurate and reliable plant disease prediction systems [33]. Furthermore, addressing the issue of computational cost and latency, particularly for resource-constrained environments, is vital for ensuring the practical applicability of these systems [29]. Finally, the development of standardized evaluation metrics and benchmarking datasets is crucial for comparing the performance of different plant disease prediction systems and driving further innovation in this field [21]. The development of systems capable of handling multiple diseases simultaneously from a single image represents another promising area of future research [29].

4. CONCLUSION

Plant disease prediction systems are rapidly evolving, driven by advancements in image processing, machine learning, and IoT technologies. These systems offer the potential to significantly improve agricultural productivity, reduce crop losses, and enhance food security. While challenges remain in developing robust and widely applicable systems, ongoing research is addressing these issues and paving the way for more accurate, efficient, and user-friendly plant disease prediction tools. The integration of various data sources, including sensor data, image data, and environmental information, coupled with sophisticated machine learning algorithms, promises to revolutionize agricultural practices and ensure sustainable crop production. The continued development and deployment of these systems are critical for meeting the growing global demand for food in a sustainable and environmentally responsible manner. Further research focusing on robustness, efficiency, accessibility, and the integration of various data streams will be crucial in realizing the full potential of plant disease prediction systems in enhancing global food security.

5. REFERENCES

[1] Vishnoi, VK, Kumar, K & Kumar, B (2021), 'Plant disease detection using computational intelligence and image processing', Journal of Plant Diseases and Protection, vol.128, pp.19–53. https://doi.org/10.1007/s41348-020-00368-0
[2] Yagnasree, S. & Jain, A. (2022). A comprehensive review of emerging technologies: machine learning and uav in crop management. https://doi.org/10.1088/1742-6596/2327/1/012035
[3] V. Udutalapally, S. P. Mohanty, V. Pallagani and V. Khandelwal, "sCrop: A Novel Device for Sustainable Automatic Disease Prediction, Crop Selection, and Irrigation in Internet-of-Agro-Things for Smart Agriculture," in *IEEE Sensors Journal*, vol. 21, no. 16, pp. 17525-17538, 15 Aug.15, 2021, doi: 10.1109/JSEN.2020.3032438
[4] Dhaka, V. S., Meena, S. V., Rani, G., Sinwar, D., Kavita, Ijaz, M. F., & Woźniak, M. (2021). A Survey of Deep Convolutional Neural Networks Applied for Prediction of Plant Leaf Diseases. *Sensors*, *21*(14), 4749. https://doi.org/10.3390/s21144749
[5] Orchi, H., Sadik, M., & Khaldoun, M. (2022). On Using Artificial Intelligence and the Internet of Things for Crop Disease Detection: A Contemporary Survey. *Agriculture*, *12*(1), 9. https://doi.org/10.3390/agriculture12010009
[6] Spatial Pyramid-Oriented Encoder-Decoder Cascade Convolution Neural Network for Crop Disease Leaf Segmentation," in *IEEE Access*, vol. 9, pp. 14849-14866, 2021, doi: 10.1109/ACCESS.2021.3052769
[7] Sibiya M, Sumbwanyambe M. Automatic Fuzzy Logic-Based Maize Common Rust Disease Severity Predictions with Thresholding and Deep Learning. Pathogens. 2021 Jan 28;10(2):131. doi: 10.3390/pathogens10020131
[8] Zhang, S., Huang, W. & Wang, H. Crop disease monitoring and recognizing system by soft computing and image processing models. *Multimed Tools Appl* **79**, 30905–30916 (2020). https://doi.org/10.1007/s11042-020-09577-z
[9] Barburiceanu, S., Meza, S., Orza, B., Malutan, R., & Terebes, R. (2021). Convolutional neural networks for texture feature extraction. Applications to leaf disease classification in precision agriculture. *IEEE Access*, *9*, 160085-160103.
[10] Khan, T. (2023). AN AGRICULTURAL INTERNET OF THINGS (A-IOT) BASED INTELLIGENT SYSTEM FOR DISEASE PREDICTION USING TRANSFER LEARNING, A CASE STUDY. *Lahore Garrison University Research Journal of Computer Science and Information Technology*, *7*(3). https://doi.org/10.54692/lgurjcsit.2023.073492
[11] Chen, H.-C., Widodo, A. M., Wisnujati, A., Rahaman, M., Lin, J. C.-W., Chen, L., & Weng, C.-E. (2022). AlexNet Convolutional Neural Network for Disease Detection and Classification of Tomato Leaf. *Electronics*, *11*(6), 951. https://doi.org/10.3390/electronics11060951

[12] Vallabhajosyula, S., Sistla, V. & Kolli, V.K.K. Transfer learning-based deep ensemble neural network for plant leaf disease detection. *J Plant Dis Prot* **129**, 545–558 (2022). https://doi.org/10.1007/s41348-021-00465-8

[13] Pravin Kumar S. K. et.al (2019), Particle Swarm Optimization (PSO) with fuzzy c means (PSO-FCM)–based segmentation and machine learning classifier for leaf diseases prediction, Wiley online library. https://doi.org/10.1002/cpe.5312

[14] Sandeep Kumar et.al (2018), "Plant Leaf Disease Identification using Exponential Spider Monkey Optimization", Sustainable Computing: Informatics and Systems (IEEE).

[15] Rina Mahakud et.al (2022), "Challenges and Solution for Identification of Plant Disease Using IoT and Machine Learning", SPECIALUSIS UGDYMAS / SPECIAL EDUCATION 2022.

[16] T. Rumpf et.al (2010), "Early detection and classification of plant diseases with Support Vector Machines based on hyperspectral reflectance", DOI: 10.1016/j.compag.2010.06.009

[17] M. S. Mustafa et. al (2019), "Development of automated hybrid intelligent system for herbs plant classification and early herbs plant disease detection", Neural Computing and Applications (Springer). https://doi.org/10.1007/s00521-019-04634-7

[18] Turkoglu, M., Yanikoglu, B.A., & Hanbay, D. (2021). PlantDiseaseNet: convolutional neural network ensemble for plant disease and pest detection. *Signal, Image and Video Processing, 16*, 301 - 309. DOI:10.1007/s11760-021-01909-2

[19] Chouhan, S.S., Kaul, A., Singh, U.P., & Jain, S. (2018). Bacterial Foraging Optimization Based Radial Basis Function Neural Network (BRBFNN) for Identification and Classification of Plant Leaf Diseases: An Automatic Approach Towards Plant Pathology. *IEEE Access, 6*, 8852-8863.

[20] Ramesh, S., & Vydeki, D. (2020). Recognition and classification of paddy leaf diseases using Optimized Deep Neural network with Jaya algorithm. Information processing in agriculture, 7(2), 249-260.

[21] Alqethami, S., Almtanni, B., Alzhrani, W., & Alghamdi, M. (2022). Disease Detection in Apple Leaves Using Image Processing Techniques. *Engineering, Technology & Applied Science Research*, *12*(2), 8335–8341. https://doi.org/10.48084/etasr.4721

[22] Sreevallabhadev Radhakrishnan, An improved machine learning algorithm for predicting blast disease in paddy crop, Materials Today: Proceedings,Volume 33, Part 1, 2020, Pages 682-686, ISSN 2214-7853, https://doi.org/10.1016/j.matpr.2020.05.802.

[23] A. Coletta, N. Bartolini, G. Maselli, A. Kehs, P. McCloskey and D. P. Hughes, "Optimal Deployment in Crowdsensing for Plant Disease Diagnosis in Developing Countries," in *IEEE Internet of Things Journal*, vol. 9, no. 9, pp. 6359-6373, 1 May1, 2022, doi: 10.1109/JIOT.2020.3002332.

[24] Chouhan, S.S., Singh, U.P. & Jain, S. Automated Plant Leaf Disease Detection and Classification Using Fuzzy Based Function Network. *Wireless Pers Commun* **121**, 1757–1779 (2021). https://doi.org/10.1007/s11277-021-08734-3

[25] Garg, D., Alam, M. (2020). Deep Learning and IoT for Agricultural Applications. In: Alam, M., Shakil, K., Khan, S. (eds) Internet of Things (IoT). Springer, Cham. https://doi.org/10.1007/978-3-030-37468-6_14

[26] V.K. Tewari, C.M. Pareek, Gurdeep Lal, L.K. Dhruw, Naseeb Singh, Image processing based real-time variable-rate chemical spraying system for disease control in paddy crop, Artificial Intelligence in Agriculture, Volume 4, 2020, Pages 21-30, ISSN 2589-7217, https://doi.org/10.1016/j.aiia.2020.01.002.

[27] Chittabarni Sarkar, Deepak Gupta, Umesh Gupta, and Barenya Bikash Hazarika. 2023. Leaf disease detection using machine learning and deep learning: Review and challenges. Appl. Soft Comput. 145, C (Sep 2023). https://doi.org/10.1016/j.asoc.2023.110534

[28] Amin, H., Darwish, A.A., Hassanien, A.E., & Soliman, M.M. (2022). End-to-End Deep Learning Model for Corn Leaf Disease Classification. *IEEE Access, 10*, 31103-31115.

[29] Hossain, S. M. M., Deb, K., Dhar, P. K., & Koshiba, T. (2021). Plant Leaf Disease Recognition Using Depth-Wise Separable Convolution-Based Models. *Symmetry*, *13*(3), 511. https://doi.org/10.3390/sym13030511

[30] Q. Zeng, X. Ma, B. Cheng, E. Zhou and W. Pang, "GANs-Based Data Augmentation for Citrus Disease Severity Detection Using Deep Learning," in *IEEE Access*, vol. 8, pp. 172882-172891, 2020, doi: 10.1109/ACCESS.2020.3025196

[31] Y. Zhao *et al*., "Plant Disease Detection Using Generated Leaves Based on DoubleGAN," in *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 19, no. 3, pp. 1817-1826, 1 May-June 2022, doi: 10.1109/TCBB.2021.3056683.

[32] Wani, J.A., Sharma, S., Muzamil, M. *et al.* Machine Learning and Deep Learning Based Computational Techniques in Automatic Agricultural Diseases Detection: Methodologies, Applications, and Challenges. *Arch Computat Methods Eng* **29**, 641–677 (2022). https://doi.org/10.1007/s11831-021-09588-5

[33] Padmapriya Dhandapani, Arulmozhi Varadarajan (2022), "Multi-Channel Convolutional Neural Network for Prediction of Leaf Disease and Soil Properties", International Journal of Intelligent Engineering and Systems, Vol.15, No.1, 2022. DOI: 10.22266/ijies2022.0228.29