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A REVIEW ON PLANT DISEASES CLASSIFICATION USING DEEP LEARNING

Abhishek Rajput[1], Unmukh Datta[2]

abhishekrajput15000@gmail.com[1], deanacademic@mpct.org[2]

Maharana Pratap College of Technology, Near Putli Ghar, Gwalior – 474006(M.P.),India.

***Abstract*-** **Deep learning's incorporation into the classification of plant diseases is a paradigm-shifting advancement in agricultural practices with far-reaching ramifications for the safety of the world's food supply. This investigation has brought to light the enormous difficulties that plant diseases present, underlining the crucial importance of early identification and accurate classification for disease management. The scalability and accuracy of traditional approaches, which rely on human judgment and subjective symptom interpretation, have been found to be lacking. Particularly, convolutional neural networks (CNNs) have emerged as game-changing tools capable of automatically understanding subtle patterns from massive plant picture collections and offering quick, scalable, and accurate disease identification solutions. Transfer learning solves data shortages and significantly improves classification accuracy by using pre-trained networks and fine-tuning them with plant disease datasets. By combining predictions from several models, lowering the likelihood of overfitting, and increasing overall accuracy, ensemble approaches like bagging and boosting improve classification resilience. Models are better able to respond to changes in image quality and lighting conditions thanks to the addition of synthetic plant images to the training dataset via Generative Adversarial Networks (GANs).On-field systems, mobile apps, remote sensing, and precision agriculture are a few examples of useful deep learning applications in plant pathology that have the potential to transform how we identify and treat plant diseases. Although there are still issues with model interpretability and data scarcity for rare diseases, deep learning's potential for classifying plant diseases is quite promising. This field supports more productive and efficient agricultural techniques in addition to better disease control, bringing us one step closer to a time when there will be more food security and less hunger throughout the world.**

Keywords- Plant Disease classification, Deep learning, Convolutional Neural Networks.

I. INTRODUCTION

The global agricultural sector plays a crucial part in sustaining human life by guaranteeing the availability of key resources including food, fiber, and everyday goods. This sector serves as the steadfast foundation on which human societies have endured for millennia, meeting our dietary needs while also supporting the economies of many countries throughout the world. The epidemic of plant diseases, however, poses a chronic and growing danger to the stability and production of this crucial industry[1].

Plant diseases can cause a great deal of damage to crops because they can be caused by a wide range of pathogens, including fungus, bacteria, viruses, and environmental factors. These illnesses have the potential to set off a series of unfavorable events, such as decreased crop yields, large financial losses for agricultural players, and, in the worst case scenario, food shortages that ripple throughout communities and entire countries[2]. In light of the world's population's rapid growth and the growing uncertainties caused by climate change, it is not only prudent but also necessary to approach this problem with the greatest efficiency and effectiveness[3].

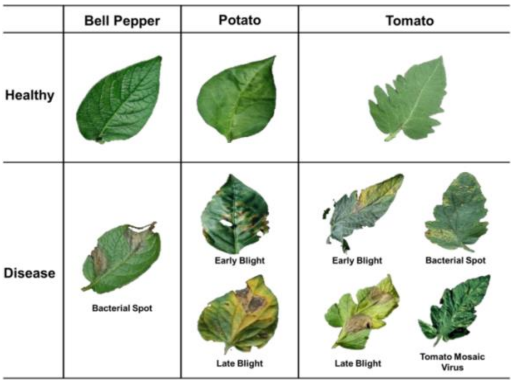

Figure 1 Plant disease Classification

Agronomists and plant pathologists have historically been largely responsible for recognizing and managing plant diseases[2]. While their wealth of knowledge and hands-on experience continues to be priceless, the complexity and massive scope of the current agricultural environment calls for more sophisticated and automated solutions. Deep learning integration, a branch of artificial intelligence, stands up in this context as a particularly promising path for agricultural innovation[4]. Positioned within the broader field of machine learning, deep learning has demonstrated impressive ability in a variety of fields, with its strength particularly evident in computer vision applications. Deep learning, which uses neural networks with numerous layers, has the inherent capacity to automatically identify subtle patterns and representations from large datasets, making it an excellent choice for image-based categorization applications[5]. The agricultural industry stands to gain from robust systems that can accurately and effectively identify and classify plant diseases based on visual indicators, including but not limited to leaf discolorations, lesions, and other symptomatic manifestations, by incorporating deep learning methodologies into the field of plant pathology[6].

This study launches a thorough investigation of the topic "Plant Diseases Classification Using Deep Learning." We will explore the many difficulties that plant diseases present, stress the importance of early detection and accurate categorization, and critically evaluate the drawbacks of conventional techniques of disease identification as we make our way through this area[7]. Our journey will gradually acquaint us with the complex world of deep learning, illuminating the fundamental ideas that underlie this technology and outlining how these ideas may be skillfully applied to build reliable and highly effective models for illness classification. Additionally, we will highlight some noteworthy developments and practical uses of deep learning in the field of plant pathology, demonstrating its transformative potential to fundamentally alter agricultural practices and significantly advance the overarching objective of ensuring global food security[8].

The Problem of Plant Illnesses

Plant diseases pose a persistent and significant problem for the agricultural industry. These diseases affect a wide range of crops, including ornamental plants, fruits, vegetables, and grains and legumes used as staple foods including rice, wheat, maize, and soybeans. Plant diseases cause a variety of symptomatic manifestations, such as wilting, leaf discolorations, blights, and stunted growth, as well as a cascade of negative effects[9]. These include severe financial losses suffered by farmers as well as crop quality and crop production reductions. Furthermore, the increased pesticide use caused by plant diseases poses serious risks to both human health and the environment.Early diagnosis and accurate classification are essential components of effective plant disease management. Farmers can take the necessary action, such as applying fungicides, enforcing quarantine rules, or making other tactical interventions, by quickly identifying diseased plants[10]. This helps to slow the spread of the illness. In addition, accurate disease classification guarantees that the chosen remedy is painstakingly tailored to treat the particular condition at hand. As a result, resource allocation is not only maximized but also negative environmental effects are reduced, making agriculture more sustainable.

The use of experienced agronomists and plant pathologists' eye inspection to identify plant diseases has been a conventional practice[11]. These specialists rely on their comprehension of disease signs, which are often visible on different plant components like leaves, stems, or fruits. Although this strategy has shown considerable effectiveness, it comes with a number of notable drawbacks:

First off, the subjective nature of human judgment adds some degree of variation to disease diagnosis, resulting in discrepancies in both the recognition of diseases and the subsequent treatment recommendations.

Second, due to the growing scale of agricultural operations, the old technique is unable to keep up with the needs of modern agriculture, which frequently call for quick and scalable disease diagnosis solutions[12].

Thirdly, diagnosing diseases manually takes time by nature, especially when done on expansive plantations or huge fields. Delays in diagnosis may allow infections to spread unchecked and exacerbate agricultural difficulties.

Furthermore, employing a team of knowledgeable professionals for ongoing crop monitoring requires a lot of resources and places a heavy load on farmers, especially small-scale farmers who do not have access to such specialized staff or financial resources[12].

The difficulty of managing disease is further complicated by the lack of readily available skilled plant pathologists, particularly in distant or developing areas, when the demand for efficient disease identification and control is greatest[13].

These significant restrictions highlight the urgent need for creative, automated, and scalable solutions to successfully address the complexities of plant disease diagnosis and categorization. Deep learning seems as a possible alternative that can change disease control strategies in agriculture because to its capacity for quick and accurate picture processing[14].

II. RELATED WORK

Kiran 2023 et. al Disease in plants Support vector machines (SVMs) and CNNs are used in the dataset to classify the dataset's images as either healthy or diseased plants, respectively, and to recommend fertilizers in accordance with the diseases of the plants. The dataset includes images of both healthy and diseased plants that were collected under controlled conditions[15].

Kanda 2022 et. al Nine typical tomato illnesses are identified using an effective deep learning algorithm. In order to identify tomato illnesses, a residual neural network technique is described. This study examines four aspects of diversity: depth size, discriminative learning rates, split ratios between training and validation data, and batch sizes. Five network depths are employed in the experimental study to gauge the network's correctness. Based on the experimental findings, the suggested technique surpassed the majority of the earlier competing methods in identifying tomato leaf disease, receiving the highest F1 score of 99.5%. A 99.23% F1 score was obtained after additional testing of our approach on the Flavia leaf picture dataset. Tobacco early light and tomato late blight are two classes of fine-grained differentiation, however the approach had the problem that part of the inaccurate forecasts were of these two classes[16].

Gaashani 2022 et. al a technique using transfer learning and feature concatenation to classify tomato leaf diseases. Using pre-trained kernels (weights) from MobileNetV2 and NASNetMobile, the authors extract features. They then combine and decrease the dimensionality of these features using kernel principal component analysis. They then integrate this information into a typical learning algorithm. The findings of the experiment support the hypothesis that concatenated features improve classifier performance. The three most common classical machine learning classifiers, random forest, support vector machine, and multinomial logistic regression, were examined by the authors. Of these, multinomial logistic regression performed the best, with an average accuracy of 97%[17].

Alshammari 2022 et. al Olive leaf disease was categorized using deep convolutional models-based binary and multiclassification systems. The outcomes are encouraging and demonstrate the potency of combining CNN and vision transformer models. According to the experimental findings presented in this article, our model surpassed the competition with an accuracy of around 96% for multiclass classification and 97% for binary classification[18].

Albattah 2022 et. al Annotations are created to identify the region of interest in the first phase. Second, a better CenterNet is shown, with DenseNet-77 being suggested for deep keypoint extraction. The one-stage detector CenterNet is used to identify and classify a number of plant diseases. We utilized the PlantVillage Kaggle database to conduct the performance study since it is the industry-standard dataset for plant illnesses and difficulties in terms of intensity fluctuations, color changes, and variances in the shapes and sizes of leaves. The offered strategy, compared to other cutting-edge methods, is more proficient and dependable in identifying and classifying plant diseases, according to both qualitative and quantitative analyses[19].

Tugrul 2022 et. al analyzed 100 of the most current CNN items over the last five years that discussed how to identify different plant leaf diseases. Additionally, we detected and compiled a number of issues and fixes related to the CNN used to identify plant leaf diseases. Deep convolutional neural networks (DCNN) trained on visual data were also the best technique for spotting early illness. We reviewed the advantages and disadvantages of using CNN in agriculture as well as the future improvements in plant disease detection[20].

Author / Year	**Method**	**Accuracy**	**Ref.**
Oishi /2021	YOLO Faster R-CNN Without	Acc= 96.7% Precision= 78.2%	[1]
Ahmed / 2021	CNN	Acc= 94%	[2]
Fenu/ 2021	VGG-16, VGG-19, ResNet50, InceptionV3, MobileNetV2 and EfficientNet	Acc= 78.31%	[21]
Rinu/ 2021	VGG16	Acc = 94.8%	[22]
Sagar/ 2021	VGG16, ResNet50, InceptionV3, InceptionResNet and DenseNet169	Acc= 98.2%	[23]

III. TYPES OF PLANT DISEASES

The term "plant diseases" refers to a broad range of ailments that can affect different anatomical parts of plants, such as their leaves, stems, roots, and fruits. These illnesses have a complex etiology that is caused by a confluence of pathogenic organisms, such as fungus, bacteria, viruses, and nematodes, as well as environmental variables, such as nutrient deficits and unfavorable weather[24]. We examine a few typical groups of plant diseases below:

- Fungal Diseases: A substantial proportion of plant diseases finds their origins in fungal pathogens. These adversaries are capable of inciting an array of maladies, ranging from the conspicuous leaf spots, rusts, and mildews to various forms of rot, including the insidious root rot and fruit rot. Exemplary instances of fungal diseases encompass powdery mildew, rust, and late blight[25].
- Bacterial Diseases: Bacteria, wielding their virulence, infiltrate plants through wounds or natural apertures, culminating in diseases such as bacterial blight, bacterial canker, and fire blight. These afflictions are often characterized by symptoms of wilting, the emergence of cankers, and the production of viscous exudates or slime.
- Viral Diseases: The minuscule agents known as viruses emerge as perpetrators of plant diseases, provoking symptoms that encompass mottled or streaked leaves, stunted growth, and the deformation of fruits. Prominent viral diseases include tomato mosaic virus and cucumber mosaic virus[26].
- Nematode Diseases: Plant-parasitic nematodes, imperceptible yet potent, insinuate themselves into plant roots, disrupting the normal course of nutrient uptake. Root-knot nematodes and cyst nematodes are emblematic instances of diseases wrought by these microscopic assailants[27].
- Oomycete Diseases: Oomycetes, resembling fungal adversaries, but biologically distinct as water molds, give rise to plant diseases like late blight and downy mildew. Such afflictions are typically characterized by leaf lesions and the degradation of plant tissues[28].
- Abiotic Diseases: Diseases stemming from non-living factors, encompassing nutrient imbalances, extreme temperature fluctuations, excessive moisture, and soil compaction, feature prominently within the ambit of plant maladies. Exemplars include nutrient deficiency disorders such as iron chlorosis and physiological anomalies like blossom end rot in tomatoes.
- Parasitic Plants: A distinctive class of plants, referred to as parasitic plants, have evolved to attach themselves directly to host plants, siphoning nutrients for their sustenance. Examples encompass dodder and broomrape.
- Insect-Transmitted Diseases: Certain diseases are disseminated by insects that serve as intermediaries or vectors. Aphids, whiteflies, and leafhoppers are commonplace vectors that transmit plant diseases such as phytoplasma disorders and specific viral infections[29].
- Fungal-Like Organisms: Beyond authentic fungi, some diseases are ascribed to fungal-like microorganisms, such as water molds, scientifically termed oomycetes, and the curious slime molds.
- Environmental Stress Diseases: These diseases materialize as a consequence of adverse environmental conditions, encompassing the rigors of drought stress, superfluous moisture that precipitates root rot, and the extremities of temperature fluctuations[30].
- Herbivore Damage: While not characterized as diseases in the traditional sense, the impairments inflicted by herbivores, including caterpillars and beetles, can enfeeble plants, rendering them susceptible to disease.

Figure 2 Plant diseases

IV. DEEP LEARNING ALGORITHMS ARE USED TO CLASSIFY PLANT DISEASES.

Deep learning-based plant disease classification provides a cutting-edge paradigm that has the potential to transform agricultural practices and strengthen global food security. With a focus on convolutional neural networks (CNNs) and transfer learning, this novel technique harnesses the impressive powers of artificial intelligence to offer an automated and amazingly accurate solution to a persistent problem in agriculture. The scalability and subjectivity of traditional approaches of plant disease identification, which rely on human skill and visual symptom recognition, are constrained[31]. The ability of deep learning models to evaluate large amounts of plant image data, quickly and effectively identifying and classifying illnesses based on visual markers, stands in stark contrast.

Utilizing their strengths in image analysis and pattern recognition, deep learning algorithms have been successfully used to classify plant diseases. The following are some of the main deep learning methods for classifying plant diseases:

1. CNNs convolutional neural networks: Convolutional Neural Networks (CNNs) have become a cornerstone in the categorization of plant diseases and are a fundamental architectural framework in the field of image-based applications. These neural networks are widely used because of their remarkable ability in recognizing complicated patterns and features inside images. They were specifically created with a focus on processing visual information. Convolutional layers, a specific layer type used by CNNs, are essential to their effectiveness[32]. In order for convolutional layers to function, convolutional operations must be applied consistently to the input image. They extract and learn hierarchical representations of features at various levels of abstraction through this process. They essentially have the ability to automatically identify the most prominent and distinguishing aspects of an image, such as minute features and minor variances, without the use of explicit feature engineering[33].
2. Transfer learning: A potent strategy to increase the efficiency of plant disease classification tasks is provided by transfer learning, a strategic paradigm within deep learning. This method makes use of deep learning models that have already been trained and have proven capable of performing challenging picture recognition tasks on large datasets, like the well-known ImageNet dataset. These pre-trained models, which frequently consist of deep convolutional neural networks (CNNs) with many layers, have developed a subtle grasp of common visual features and patterns.Transfer learning takes two forms when it comes to classifying plant diseases. The core architecture is initially a pre-trained model that has

already completed significant training on a diverse dataset like ImageNet. Then, to particularly address the complexities of plant disease recognition, this pre-trained model is modified, or fine-tuned. This fine-tuning procedure entails modifying the model's internal parameters while subjecting it to a dataset of plant diseases, which may be smaller in scale than the initial ImageNet dataset[20].

3. Data Augmentation: The variety of the training dataset is artificially increased using data augmentation techniques. In order to create more training examples, these algorithms alter the original images by rotating, flipping, and scaling them. The resilience and generality of models are enhanced by the addition of data.
4. Ensemble Learning: To improve the classification performance of models for the detection of plant diseases, ensemble approaches provide a sophisticated deep learning approach. These methods are built on the idea of merging the predictions from various unique deep learning models, each of which may be based on a different architecture, training set, or initial conditions. The main goal is to use the combined knowledge of these several models to make a final prediction that is more reliable and accurate.
5. Recurrent Neural Networks (RNNs): RNNs are employed in situations where sequential data is present, such as the analysis of time-series data pertaining to plant diseases, whereas CNNs are typically used for picture classification. RNNs are capable of identifying temporal connections and patterns in illness development.
6. Generative Adversarial Networks (GANs): In the area of classifying plant diseases, Generative Adversarial Networks (GANs) present a strong deep learning approach for augmenting and extending training datasets. A generator and a discriminator are the two neural networks that interact dynamically in GANs to perform their functions. Through this adversarial process, synthetic data that closely resembles the training dataset's real-world samples is produced[34]. GANs can be used to create synthetic images of both healthy and ill plants in the field of classifying plant diseases. This artificial data augmentation serves a variety of useful functions.

V. CONCLUSION

In conclusion, the use of deep learning to the classification of plant diseases represents a revolutionary development in agricultural methods and has the potential to dramatically enhance global food security. This analysis has shed light on the daunting difficulties that plant diseases present, highlighting the critical importance of early identification and accurate classification for disease management.The scalability and accuracy of traditional approaches, which rely on human judgment and subjective symptom interpretation, have been found insufficient. Convolutional neural networks (CNNs), in particular, have emerged as a game-changing deep learning technique that is able to understand complex patterns on its own from huge databases of plant images. Rapid, scalable, and objective solutions for identifying plant diseases are provided by this integration.By utilizing pre-trained networks and refining them on plant disease datasets, transfer learning addresses the issue of data scarcity and significantly boosts classification accuracy. It also expands the capabilities of deep learning models.By pooling predictions from various models, lowering the chance of overfitting, and improving overall accuracy, ensemble approaches like bagging and boosting give the classification process robustness.By using Generative Adversarial Networks (GANs) to create synthetic plant images, the training dataset is enriched, allowing models to more easily adapt to changes in image quality and lighting.The way we identify and control plant diseases may change as a result of practical deep learning applications in plant pathology, including on-field systems, mobile apps, remote sensing, and precision agriculture.Although there are still issues with model interpretability and data scarcity for rare diseases, the trajectory of plant disease classification using deep learning is quite positive. In addition to offering better disease control, this field supports more productive and efficient agricultural practices, bringing us one step closer to a time when there will be greater food security and less hunger around the world.

REFERENCES

[1] Y. Oishi *et al.*, "Automated abnormal potato plant detection system using deep learning models and portable video cameras," *Int. J. Appl. Earth Obs. Geoinf.*, vol. 104, p. 102509, 2021, doi: 10.1016/j.jag.2021.102509.

[2] A. A. Ahmed and G. Harshavardhan Reddy, "A Mobile-Based System for Detecting Plant Leaf Diseases Using Deep Learning," *AgriEngineering*, vol. 3, no. 3, pp. 478–493, 2021, doi: 10.3390/agriengineering3030032.

[3] S. S. Harakannanavar, J. M. Rudagi, V. I. Puranikmath, A. Siddiqua, and R. Pramodhini, "Plant leaf disease detection using computer vision and machine learning algorithms," *Glob. Transitions Proc.*, vol. 3, no. 1, pp. 305–310, 2022, doi: 10.1016/j.gltp.2022.03.016.

[4] J. Zhang, Y. Rao, C. Man, Z. Jiang, and S. Li, "Identification of cucumber leaf diseases using deep learning and small sample size for agricultural Internet of Things," *Int. J. Distrib. Sens. Networks*, vol. 17, no. 4, 2021, doi: 10.1177/15501477211007407.

[5] R. Sarwar, M. Aslam, K. S Khurshid, T. Ahmed, A. Maria Martinez-Enriquez, and T. Waheed, "Detection and Classification of Cotton Leaf Diseases Using Faster R-CNN on Field Condition Images," *Acta Sci. Agric.*, vol. 5, no. 10, pp. 29–37, 2021, doi: 10.31080/asag.2021.05.1066.

[6] P. Singh, A. Verma, and J. S. R. Alex, "Disease and pest infection detection in coconut tree through deep learning techniques," *Comput. Electron. Agric.*, vol. 182, no. January, p. 105986, 2021, doi: 10.1016/j.compag.2021.105986.

[7] A. T. Madhavi and C. S. SVijayasundar, "Detection of Leaf Disease Using Convolutional Neural Network," no. 7, pp. 2394–0697, 2020.

[8] H. Hong, J. Lin, and F. Huang, "file:///F:/MSCS/Advanced topics in AI/review paper/Wheat Disease Detection Using Image Processing .pdf," *Proc. - 2020 Int. Conf. Big Data, Artif. Intell. Internet Things Eng. ICBAIE 2020*, pp. 25–29, 2020.

[9] M. Lambat, R. Kothari, M. Kabi, and T. Mane, "Plant Disease Detection Using InceptionV3," *Int. Res. J. Eng. Technol.*, vol. 9, no. 6, pp. 2295–2300, 2022, [Online]. Available: www.irjet.net

[10] A. Mushtaq, A. Karol, D. Gulhane, T. Chandiwade, and B. E. Student, "International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering Plant Disease Detection using CNN & Remedy," pp. 622–626, 2019, doi: 10.15662/IJAREEIE.2019.0803014.

[11] P. Bharali, C. Bhuyan, and A. Boruah, "Plant disease detection by leaf image classification using convolutional neural network," *Commun. Comput. Inf. Sci.*, vol. 1025 CCIS, pp. 194–205, 2019, doi: 10.1007/978-981-15-1384-8_16.

[12] V. K. Shrivastava, M. K. Pradhan, S. Minz, and M. P. Thakur, "Rice plant disease classification using transfer learning of deep convolution neural network," *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. - ISPRS Arch.*, vol. 42, no. 3/W6, pp. 631–635, 2019, doi: 10.5194/isprs-archives-XLII-3-W6-631-2019.

[13] P. A. Toshik Chauhan, "Plant Leaf Detection and Disease Identification System," *Int. J. Sci. Eng. Res. Vol.*, vol. 13, no. 6, pp. 944–948, 2022.

[14] S. K. Sanju, "An Automated Detection and Classification of Plant Diseases from the Leaves Using Image processing and Machine Learning Techniques: A State-of-the-Art Review," *Ann. R.S.C.B*, vol. 25, no. 4, pp. 15933–15950, 2021, [Online]. Available: http://annalsofrscb.ro

[15] A. Kiran, S. K. Lokesh Naik, M. S. Raj, and S. K. Palvadi, "Plant Disease Detection using Image Processing with Machine Learning," *2023 4th Int. Conf. Electron. Sustain. Commun. Syst. ICESC 2023 - Proc.*, pp. 1590–1595, 2023, doi: 10.1109/ICESC57686.2023.10192986.

[16] P. S. Kanda, K. Xia, A. Kyslytysna, and E. O. Owoola, "Tomato Leaf Disease Recognition on Leaf Images Based on Fine-Tuned Residual Neural Networks," *Plants*, vol. 11, no. 21, 2022, doi: 10.3390/plants11212935.

[17] M. S. A. M. Al-gaashani, F. Shang, M. S. A. Muthanna, M. Khayyat, and A. A. Abd El-Latif, "Tomato leaf disease classification by exploiting transfer learning and feature concatenation," *IET Image Process.*, vol. 16, no. 3, pp. 913–925, 2022, doi: 10.1049/ipr2.12397.

[18] H. Alshammari, K. Gasmi, I. Ben Ltaifa, M. Krichen, L. Ben Ammar, and M. A. Mahmood, "Olive Disease Classification Based on Vision Transformer and CNN Models," *Comput. Intell. Neurosci.*, vol. 2022, 2022, doi: 10.1155/2022/3998193.

[19] W. Albattah, M. Nawaz, A. Javed, M. Masood, and S. Albahli, "A novel deep learning method for detection and classification of plant diseases," *Complex Intell. Syst.*, vol. 8, no. 1, pp. 507–524, 2022, doi: 10.1007/s40747-021-00536-1.

[20] B. Tugrul, E. Elfatimi, and R. Eryigit, "Convolutional Neural Networks in Detection of Plant Leaf Diseases: A Review," *Agric.*, vol. 12, no. 8, 2022, doi: 10.3390/agriculture12081192.

[21] G. Fenu and F. M. Malloci, "Using Multioutput Learning to Diagnose Plant Disease and Stress Severity," *Complexity*, vol. 2021, 2021, doi: 10.1155/2021/6663442.

[22] R. R and M. S H, "Plant Disease Detection and Classification using CNN," *Int. J. Recent Technol. Eng.*, vol. 10, no. 3, pp. 152–156, 2021, doi: 10.35940/ijrte.c6458.0910321.

[23] A. Sagar and D. Jacob, "On Using Transfer Learning For Plant Disease Detection," *bioRxiv*, p. 2020.05.22.110957, 2021, [Online]. Available: https://www.biorxiv.org/content/10.1101/2020.05.22.110957v2%0Ahttps://www.biorxiv.org/content/10.1101/2020.05.22.110957v2.abstract

[24] M. Francis and C. Deisy, "Disease Detection and Classification in Agricultural Plants Using Convolutional Neural Networks - A Visual Understanding," *2019 6th Int. Conf. Signal Process. Integr. Networks, SPIN 2019*, pp. 1063–1068, 2019, doi: 10.1109/SPIN.2019.8711701.

[25] M. Sardogan, A. Tuncer, and Y. Ozen, "Plant Leaf Disease Detection and Classification Based on CNN with LVQ Algorithm," *UBMK 2018 - 3rd Int. Conf. Comput. Sci. Eng.*, pp. 382–385, 2018, doi: 10.1109/UBMK.2018.8566635.

[26] Institute of Electrical and Electronics Engineers, "ICIRD 2018 : 2018 IEEE International Conference on Innovative Research and Development : May 11, 2018, AIT Conference Center Bangkok, Thailand.," *2018 IEEE Int. Conf. Innov. Res. Dev.*, no. May, pp. 1–6, 2018.

[27] S. Shammi, F. Sohel, D. Diepeveen, S. Zander, and M. G. K. Jones, "A survey of image-based computational learning techniques for frost detection in plants," *Inf. Process. Agric.*, vol. 10, no. 2, pp. 164–191, 2023, doi: 10.1016/j.inpa.2022.02.003.

[28] S. Wallelign, M. Polceanu, and C. Buche, "Soybean plant disease identification using convolutional neural network," *Proc. 31st Int. Florida Artif. Intell. Res. Soc. Conf. FLAIRS 2018*, pp. 146–151, 2018.

[29] V. R. T and S. R. K, "Plant Disease Detection using Advanced Convolutional Neural Networks with Region of Interest Awareness," *J. Immunol. Res. Reports*, pp. 1–7, 2022, doi: 10.47363/jirr/2022(2)117.

[30] K. L. Narayanan *et al.*, "Banana Plant Disease Classification Using Hybrid Convolutional Neural Network," *Comput. Intell. Neurosci.*, vol. 2022, 2022, doi: 10.1155/2022/9153699.

[31] S. Talasila, K. Rawal, G. Sethi, S. MSS, and S. P. R. M, "Black gram Plant Leaf Disease (BPLD) dataset for recognition and classification of diseases using computer-vision algorithms," *Data Br.*, vol. 45, p. 108725, 2022, doi: 10.1016/j.dib.2022.108725.

[32] L. Falaschetti, L. Manoni, D. Di Leo, D. Pau, V. Tomaselli, and C. Turchetti, "A CNN-based image detector for plant leaf diseases classification," *HardwareX*, vol. 12, p. e00363, 2022, doi: 10.1016/j.ohx.2022.e00363.

[33] P. Tiwari *et al.*, "CNN Based Multiclass Brain Tumor Detection Using Medical Imaging," *Comput. Intell. Neurosci.*, vol. 2022, 2022, doi: 10.1155/2022/1830010.

[34] N. Kundu *et al.*, "Disease detection, severity prediction, and crop loss estimation in MaizeCrop using deep learning," *Artif. Intell. Agric.*, vol. 6, pp. 276–291, 2022, doi: 10.1016/j.aiia.2022.11.002.