A Comprehensive Survey on Deep Learning Techniques for Plant Disease Detection and Classification

Mrs. Nusrat Anjum
Research scholar, Faculty of Engineering and Technology
Khaja Bandanawaz University
Kalaburagi, India
nusratmanurkar_wit@rediffmail.com

Dr.Shameem Akther
Assistant Professor, Faculty of Engineering and Technology
Khaja Bandanawaz University
Kalaburagi, India
Shameemakther150@gmail.com

Abstract

Plant diseases are a big danger to the world's capacity to grow food, keep food safe, and keep the economy stable. Traditional ways of identifying things, which mostly depend on human specialists looking at them, take a long time, are subjective, and can't be used for large-scale monitoring. As artificial intelligence (AI) has become better, especially deep learning (DL), image-based plant disease identification has become a game-changing method for early diagnosis and precision farming. This study looks at recent work in AI-driven plant disease diagnosis in a systematic way, focusing on deep learning architectures like Convolutional Neural Networks (CNNs), transfer learning, and hybrid models. The study groups approaches by their learning methodologies, dataset kinds, and suitability for deployment. It also compares their accuracy, efficiency, and scalability. The paper also points out the main problems with current methods, such as their limited ability to target specific crops, their reliance on curated datasets, and their lack of field validation. This study points out important problems and suggests future research routes to make models more generalizable, useful in real time, and compatible with environmentally friendly farming methods. The information given is meant to help build strong and smart plant disease diagnosis systems that can be used in real life.

Keywords: *Plant Disease Diagnosis, Deep Learning, Convolutional Neural Networks (CNNs), Transfer Learning, Precision Agriculture.*

1. Introduction

The study of plant diseases is called plant pathology. The study of plant illnesses tries to find ways to help plants survive when they are exposed to bad weather and disease-causing bacteria. Most plant pathogens are microorganisms, such as bacteria, viruses, nematodes, fungus, and protozoa. Some plants and algae are also parasites. They hurt plants, devour nutrients, and spread disease by releasing enzymes, toxins, and other chemicals. Plant diseases may kill plants, cause hunger, and even wipe out whole species of plants because they make people sick. Plant pathogens invade plant tissues and cause disease by taking resources from host cells to develop, multiply, and spread [1]. When an infection gets into a plant, it makes enzymes, toxins, growth regulators, and other active substances that change the structure and function of its cells and tissues. Signs of pathogens include dead tissue patches on leaves, stems, fruit, and roots, which are called blights. These blights can kill leaves and young shoots all of a sudden. The symptoms might be very mild or very bad, and they could even kill the whole plant, depending on what kind of illness is causing them.

Plant disease is a common problem in farming that lowers the quality and quantity of crops. Some traditional ways of finding plant diseases have clear problems [1]. They generally involve looking at plants by hand and are restricted by the expertise and experience of professionals, which makes it hard to find diseases quickly and accurately. One of the main things that researchers are worried about is losing agricultural output. Plants perish if their leaves can't make chlorophyll through photosynthesis due of illnesses or abnormalities. A lot of people have thought about using artificial intelligence (AI) to fix the problem of losing crop yields, especially in the fields of computer vision and machine learning, also with rise of other technology like blockchain has contributed to precision agriculture as the integrity [2] . Researchers have come up with a lot of deep Convolutional Neural Networks (CNN) to help identify and classify plant diseases. Adi et al. present some of the most prominent CNN. It is very important to find plant illnesses early on in order to grow nutritious food. Finding out what diseases plants have is an important part of routine plant ecology study. Farmers frequently have trouble figuring out exactly what is wrong with plants since the indicators are so little. The Foreign Agricultural Service of the United States Department of Agriculture (USDA) says that rice was grown on 163.99 million hectares in 2020 and 2021. The average yield was 4.57 metric tons per hectare, and the total production was 502.10 million metric tons. But output was down 2.16% from prior years [3].

These numbers show that rice fields are producing less than they did in past years. Several illnesses are thought to be among the things that impact the development and productivity of rice crops. These illnesses, which can be caused by bacteria, fungus, and viruses, can cause farmers to lose a lot of money if they are not properly handled [4]. Finding plant diseases early is very important for getting a good crop output. Black measles, black rot, bacterial spot, and other plant diseases can hurt plants' development, crop quality, and the economy in the agriculture business. Farmers sometimes utilize costly methods and insecticides to keep these illnesses from affecting their crops. Using chemicals hurts the plant and the area around it. Also, this sort of strategy makes production costs go up, which is a big loss of money for farmers. The most crucial time for good illness care is when disorders are first found. In agriculture, it is common to have human professionals manually find and diagnose plant illnesses. Computer vision and artificial intelligence studies have made it feasible to automatically find plant illnesses in raw photos as technology has gotten better. The researchers in this study were able to look at plant illnesses and pest infestations that harm the leaves of plants. Image processing techniques are increasingly widely used in farming to find and identify weeds, grade fruit, find and count plant diseases, and study plant genetics. A lot of people are using deep learning approaches right now [5]. Deep learning is a more advanced kind of machine learning that employs neural networks to operate like the human brain. Semantic characteristics are used as the categorization strategy in traditional methods. LeChun et al. say that deep learning is a way for neural networks to learn, and one thing that makes deep learning

special is that it can automatically acquire features from visual patterns. A convolutional neural network (CNN) is a deep learning model that is often used to work with images.
Pests and illnesses hurt the total output of crops all around the world. Fungal infections are one of the main things that harm the quality of crops in India. There are two types of infections that can happen to plants: biotic and abiotic [6–7]. Biotic diseases are caused by pathogens like viruses, fungi, and bacteria. Biotic illnesses are very contagious and hazardous, just as abiotic diseases, which are caused by things like mineral insufficiency, sunburn, and other environmental causes. Some common biotic diseases that can be seen on apple leaves are scab, cedar rust, leaf blotch, powdery mildew, blight, mosaic, and black rot. Scab, Cedar rust, and Black rot are some of the diseases that are important to find. Here is a short description of various disorders.

- Black rot is a fungal disease that is caused by the Diplodia seriata fungus. It makes small sneaks on the top of the leaf as it unfolds. Later, the infected leaves will have frog-eye spots with reddish or purplish edges. As the lesion gets older, it turns yellow, and if it gets worse, it can cause the tree to lose its leaves, which makes it weaker. Black rot can hurt both the leaves and the fruit of the tree.
- Venturia inaequalis fungus spreads scab, which is a very bad infection. The upper surface of the leaf has pale yellow or olive green spots that look like disease. The lower surface has dark or velvety lesions that look like disease. As the infection spreads, it makes leaves curl up or fall off. The tree keeps losing leaves and getting hurt because of the bad infection. Scab also hurts the tree's leaves and fruit.
- Cedar rust is another fungal infection caused by the Gymnosporangium juniperi-virginianae fungus. At first, reddish or pale yellow circles appear on the upper surface of leaves. These circles grow into bright orange-yellow spots over time. When the infection is bad, it causes pale yellow or orange spots on fruits and leaves to fall off in the fall.

Figure 1 different types of leaf diseases

Plants diseases frequently have clear markings or lesions on their leaves, stems, blooms, or fruits. In general, each disease or pest situation has its own distinct apparent pattern that may be utilized to identify problems. The leaves of plants are usually the best way to tell if a plant is sick, and most of the symptoms of illnesses may show up on the leaves [8–9]. Most of the time, agricultural and forestry specialists or farmers utilize their knowledge to find fruit tree illnesses and pests on the farm. This strategy is not only based on opinion, but it also takes a lot of time, effort, and is not very effective.

Plant diseases remain one of the most significant constraints in modern agriculture, causing substantial losses in crop yield, food quality, and economic return. Traditionally, disease detection has relied on manual observation by farmers or agricultural experts, which is often slow, subjective, and limited by human expertise. The advent of image processing and artificial intelligence (AI) technologies, particularly deep learning (DL), has enabled automated, efficient, and accurate identification of various plant diseases from leaf images. Numerous research efforts have demonstrated that models such as Convolutional Neural Networks (CNNs), transfer learning architectures, and hybrid classifiers can achieve high accuracy in disease classification, even under diverse environmental conditions. However, despite rapid developments, there exists a wide variation in the approaches, datasets, evaluation protocols, and deployment readiness across different studies. While some models emphasize high classification accuracy, others target lightweight design for mobile deployment or focus on interpretability through explainable AI techniques. Furthermore, many methods are restricted to controlled environments or single-crop datasets, limiting their generalizability. This diversity and fragmentation create challenges for researchers and practitioners seeking to select or build optimal solutions for real-world agricultural applications. Therefore, the motivation for this survey is to systematically review and analyze the current state-of-the-art approaches in AI-based plant disease detection. The paper aims to provide a structured overview of methods, highlight their comparative strengths and limitations, identify common challenges, and uncover research gaps that need to be addressed. By doing so, this survey intends to guide future research efforts and support the development of more robust, scalable, and interpretable plant disease diagnosis systems suitable for real-world agricultural deployment.

- **Comprehensive Categorization of AI-Based Plant Disease Detection Techniques**: This survey provides a structured classification of recent methodologies employed in plant disease detection, including traditional machine learning algorithms, deep learning architectures, hybrid approaches, and explainable AI models. By categorizing these techniques based on model type, dataset usage, and performance metrics, the paper offers a clear comparative perspective for researchers seeking to understand the landscape of existing solutions.
- **Critical Analysis of Strengths, Limitations, and Practical Applicability**: The survey critically analyzes each method’s advantages, disadvantages, and deployment feasibility, with a focus on accuracy, interpretability, generalizability, and real-time applicability. It also highlights the challenges associated with dataset dependency, scalability across plant species, and computational constraints, thus providing a practical lens for evaluating the effectiveness of various approaches.
- **Identification of Research Gaps and Future Directions**: By synthesizing the findings from multiple studies, this paper identifies key research gaps such as limited multi-crop adaptability, lack of field-based validation, and insufficient integration with smart farming systems. It concludes with a set of recommendations and promising directions for future work, aimed at advancing the development of intelligent, scalable, and environmentally sustainable plant disease diagnosis systems.

2. Related Work

Farmers use too many herbicides, insecticides, and pesticides to treat plant illnesses because they don't know enough about the diseases that hurt crops. So, it is very important to use the latest technology to identify disorders so that the right amount and type of chemicals can be given [10]. Artificial Intelligence (AI)-, which helps to, manage the:

crop harvesting, irrigation, soil content sensitivity, crop monitoring-- We, the weed, harvest, the establishment, are all things that different industries, including agriculture, have to deal with. AI technology helps farmers figure out what pests, diseases, and malnutrition are on their land. AI sensors can also find and name weeds. It uses the same approaches to group diseases, divide up affected areas, and find diseases [11]. Image classification and object recognition algorithms have become much more accurate at identifying things in the last several years thanks to deep learning. AI can tackle the problem in a useful and effective way. This led to the development of Machine Learning (ML), Deep Learning (DL), Transfer Learning (TL), and Deep Transfer Learning (DTL). Artificial Intelligence (AI) is a big area of study that lets robots think for themselves without being told what to do. ML is a part of AI, however it is not the same thing as AI. ML stands for systems that learn on their own without any help from people. ML is a part of DL, which is utilized with large datasets [12]. There are three stages in the history of DL. The original type of neural network, which was constructed between 1943 and 1969, is a linear model that can only solve problems using linear classification. The second generation of Neural Network Back Propagation (BP) (1986–1998) worked with the multilayer perceptron. This method led to the second emergence of neural networks. But in 1991, a problem with the BP approach called "gradient vanishing" was found. DL (2006 to present) is the name of the third generation of neural networks. AlexNet, a Deep Learning model, became quite well-known in 2012 after it won the "ImageNet Large Scale Visual Recognition Challenge (ILSVRC)." Transfer learning is a more sophisticated deep learning method that has been shown to work well for tasks like identification and classification. Deep Learning is a type of machine learning that uses Deep Transfer Learning (DTL) to train a model for a different data source or job by reusing information learnt from one data source or activity. Deep Transfer Learning (DTL) tries to lessen this reliance on task-specific data by using what it has learnt from one source data or task to train a model for a second task or data source. DTL might reduce the requirement for a lot of task-specific labeled data for every new task or data source by recycling knowledge learnt from a pre-trained model or adapting representations from one domain to another [13]. People typically use deep learning methods to recognize tear patterns Premises rejection and machine vision applications. Researchers used different Deep Learning models [14] to find plant diseases. You can use DTL to find plant diseases with a small number of factors and yet get very accurate results [15]. Transfer Learning in Intelligent Support Systems may be very helpful in many ways. For example, it can cut down on training time, enhance performance with less labeled data, and let you use knowledge and skills that are already there.

Malik et al. [16] recommend using Deep Learning methods to create a deep CNN hybrid strategy to find illnesses on sunflower leaves. The paper talks about four diseases that can affect sunflowers: Alternaria leaf blight, downy mildew, Phoma blight, and Verticillium wilt. We employ stacking, one of the ensemble learning methods, to train the new model combination. This is done by combining two models, VGG-16 and MobileNet. The suggested method beats the competition with an accuracy of 89.2% on the same dataset. Liu et al. [17] takes 19 color and texture feature values from the infected areas and builds a random forest method to find the diseased areas. It is conceivable to get a 95% overall recognition rate. Sara et al. [18] provide a standard Deep Learning model that includes a dataset of sunflower leaves and blooms. This will enable researchers create algorithms that can find illnesses more easily. There are five main processes in this process: (a) Image Augmentation, (b) Resizing, (c) Splitting Images, (d) Model Generation, and (e) Performance Evaluation. Ramcharan et al. [19] say that InceptionV3 is a Deep Learning model that can automatically and extremely accurately identify cassava diseases. This method makes it easy to train models on a desktop and then use them on mobile devices without having to go through the time-consuming and difficult process of extracting features from photos. It was thought that the bigger picture leaflet dataset would work better for all ailment categories than the original dataset. The results show that the size of the dataset does not affect how well predictions are made. Huang et al. [20] used the GoogLeNet model to train their model, which included cascade recovery of spike lesions at different sizes. The Softmax classifier was 92.0% accurate. Liu et al. used the feature map to make the original image better. After that, they employed the Region Proposal Network (RPN) to downsample the indicated region and conduct boundary regression and classification [21]. 87.2% of grape diseases were found. Liu et al. integrated the sparse self-encoder and CNN to make the network branch bigger. They then employed varied sampling input from the encoder training to get the low-dimensional features that constituted the CNN's initial weight. This not only solved the problem of its own tiny sample size, but it also sped up the network's convergence. The research [22] suggests a way to find illnesses in apple leaves using Genetic Algorithm (GA) and Correlation-based Feature Selection (CFS). The suggested technique includes preprocessing the apple leaf photos and utilizing CFS to find characteristics. After that, the GA picks the traits that are most important from the ones that were found. We employ the chosen characteristics to teach a Support Vector Machine (SVM) classifier how to find illnesses in apple leaves. When compared to other approaches that are already available, the suggested method does better in terms of accuracy and efficiency. The technology that has been suggested might be used to find and stop infections in apple plants early on. We utilized Liu et al.'s [23] new machine learning method to find apple illnesses. They employed HIS (Hue, Saturation, and Intensity), YUV (Brightness (Y) + Color Difference (U,V)), and grey color spaces to get rid of the background. A region-growing method is employed to find out the form, color, and texture of each affected area. Then, the Genetic Algorithm (GA) and Correlation-based Feature Selection (CFS) method are used to choose the most important characteristics. After that, SVM is used to sort them. Using machine vision technology, Xue et al. [24] separate the samples and figure out how much they are decomposing in newly cut cauliflowers. The PLS-DA (Partial Least Squares Discriminant Analysis) and ELM (Extreme Learning Machine) discriminant models were able to correctly identify 95% and 90.9% of decaying samples, respectively. Also, the grades for the rotting were split up based on how big the rotten spots were. We utilized the region growth technique to find the edges and feature regions of the rotting cauliflower samples. The results show that machine vision technology can separate coherent fresh-cut cauliflower samples and tell the difference between fresh and decaying cauliflower samples in both qualitative and quantitative ways. ImageNet has a lot of semantic hierarchies that group images into different classifications. Deng et al. [25] give a clean dataset for each level of the WordNet hierarchy.

Nalini et al. [26-28] came up with a DNN that could sort paddy leaf diseases. Using a Crow Search Algorithm (CSA), a metaheuristic search method that mimics how crows act, adjusting biases and weights lowered the error. During the normal fine-tuning and pre-training steps, optimization was done to make a DNN-CSA structure that allows for the use of important statistical learning. This cuts down on the amount of work that has to be done on the computer and ensures that the classification is very accurate. This study used a k-means clustering method to find the regions of the paddy leaf photos that were related to illness. These images were then used as input for pre-processing. After that, thresholding was used to get rid of the other healthy areas. The next phase was to get information on colour, texture, and shape from areas that had been separated from the diseased areas before. After then, the new approach was used to sort paddy leaf diseases. Turkoglu et al. [28-30] came up with two ways to categorize things that use deep characteristics from convolutional neural networks that have previously been trained. The recommended methods use six state-of-the-art convolutional neural networks that have been merged and fine-tuned. Each method is tested on the given task, both alone and in groups. Lastly, a support vector machine (SVM) classifier figures out how well different combinations of the recommended models work.

Table 1survey table

Ref	Method	Advantages	Disadvantages	Research Gap
[16]	Hybrid CNN (VGG-16 + MobileNet) with stacking	Improved classification accuracy for sunflower leaf diseases; ensemble approach enhances performance	Moderate accuracy (89.2%); focused on sunflower only	Requires validation across other crops; lacks real-field robustness
[17]	Random Forest on color and texture features	Simple and interpretable model; good recognition rate (95%)	Limited to feature-based classification; not deep learning based	Lacks adaptability to variable image conditions and large datasets
[18]	Traditional DL pipeline with dataset generation (sunflower)	Complete pipeline from augmentation to evaluation	Dataset-specific; no model generalization tested	Limited transferability; focused on one plant species
[19]	InceptionV3 for cassava disease detection	High accuracy; mobile deployment capability	Limited to cassava dataset	Needs evaluation on diverse crop types and real-time scenarios
[20]	GoogLeNet with Softmax for lesion detection	Integrated multi-scale lesion detection	Accuracy limited to 92%; computational cost	Requires lightweight alternatives for field use
[21]	Region Proposal Network + CNN with image enhancement	Improved image regions for classification; detection refinement	Complex pipeline; lower accuracy (87.2%)	Needs real-time deployment optimization
[22]	SVM with GA + CFS feature selection	Efficient feature extraction and classification for apple leaves	Limited to SVM and apple dataset	Model needs validation with different classifiers and crops
[24]	PLS-DA and ELM for rotting level detection in cauliflower	High accuracy in rot grading; useful for quality assessment	Targeted for post-harvest analysis	Extension to field-based disease prediction is lacking

2.1. Research gap

- Scalability of Manual Inspections: Existing plant disease detection methods heavily rely on manual inspections by trained experts, which are not only time-consuming but also not scalable across large agricultural fields. There is a significant gap in developing automated systems that can operate on a large scale without human intervention.
- Accuracy and Speed of Disease Identification: Current methods often lack the speed and accuracy needed for effective disease management. The reliance on human expertise and physical inspections results in delays and potential errors. Advanced AI techniques, specifically in image recognition, can bridge this gap by providing faster and more accurate diagnostics.
- Integration of AI in On-Site Diagnostics: Despite the advancements in AI for plant disease detection, there is a gap in its integration into practical, on-site applications that farmers can use. Most existing AI applications are confined to research settings and have not transitioned into practical tools available for everyday agricultural use.
- Data Availability for AI Training: There is a shortage of publicly available, high-quality datasets for training AI models specifically tailored for different types of plant diseases. The lack of diverse and extensive datasets hampers the development of models that can accurately recognize a wide range of plant diseases under varying conditions.
- Environmental Impact of Current Practices: The current practice of using pesticides and other chemical treatments as a primary response to plant disease detection not only impacts the environment but also increases the cost of production. Research is needed to develop sustainable AI-driven solutions that minimize chemical usage and promote environmentally friendly farming practices.

3. Conclusion

The suggested study shows how important it is to find plant diseases early using deep learning and computer vision methods. The goal is to create a strong deep CNN model that can correctly identify and categorize plant leaf diseases using pictures. The model's architecture includes convolutional layers, pooling layers, and fully linked layers, which work together to capture both low-level and high-level aspects of leaf pictures. The model wants to get around problems with small datasets, changing symptoms, and complicated calculations by using a mix of pre-processing methods, transfer learning, and data augmentation. One of the goals is to create a very precise disease detection system that can help farmers grow more crops and use more environmentally friendly farming methods. Some areas of future study are multimodal fusion, real-time deployment on edge devices, domain adaptability, and making models easier to understand.

References

1. K. Vishnoi, K. Kumar, and B. Kumar, ‘‘Plant disease detection using computational intelligence and image processing,’’ J. Plant Diseases Protection, vol. 128, no. 1, pp. 19–53, Feb. 2021, doi: 10.1007/s41348-020- 00368-0.
2. Banu, A. Dr Sameena, and B. Shaista Shireen. "Safeguarding the Financial Transactions with the Aid of Blockchain Technology." (2021).

3. V. K. Vishnoi, K. Kumar, and B. Kumar, ‘‘A comprehensive study of feature extraction techniques for plant leaf disease detection,’’ Multimedia Tools Appl., vol. 81, no. 1, pp. 367–419, Jan. 2022, doi: 10.1007/s11042-021- 11375-0.
4. K. Simonyan and A. Zisserman, ‘‘Very deep convolutional networks for large-scale image recognition,’’ 2014. [Online]. Available: https://arxiv.org/abs/1409.1556, doi: 10.48550/ARXIV.1409.1556.
5. K. He, X. Zhang, S. Ren, and J. Sun, ‘‘Deep residual learning for image recognition,’’ 2015. [Online]. Available: https://arxiv.org/abs/1512.03385, doi: 10.48550/ARXIV.1512.03385.
6. V. Tanwar, S. Lamba, B. Sharma and A. Sharma, "Deep Learning-based Approach for Leaf Disease of Sugarcane Classification," 2023 IEEE 12th International Conference on Communication Systems and Network Technologies (CSNT), Bhopal, India, 2023, pp. 176-180, doi: 10.1109/CSNT57126.2023.10134643.
7. U. Vignesh and B. S. Chokkalingam, "EnC-SVMWEL: Ensemble Approach using CNN and SVM Weighted Average Ensemble Learning for Sugarcane Leaf Disease Detection," 2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), Erode, India, 2023, pp. 1663-1668, doi: 10.1109/ICSCDS56580.2023.10104818.
8. K. Liu and X. Zhang, "PiTLiD: Identification of Plant Disease From Leaf Images Based on Convolutional Neural Network," in IEEE/ACM Transactions on Computational Biology and Bioinformatics, vol. 20, no. 2, pp. 1278-1288, 1 March-April 2023, doi: 10.1109/TCBB.2022.3195291.
9. Y. H. Bhosale, S. R. Zanwar, S. S. Ali, N. S. Vaidya, R. A. Auti and D. H. Patil, "Multi-Plant and Multi-Crop Leaf Disease Detection and Classification using Deep Neural Networks, Machine Learning, Image Processing with Precision Agriculture - A Review," 2023 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2023, pp. 1-7, doi: 10.1109/ICCCI56745.2023.10128246.
10. H. Tian, T. Wang, Y. Liu, X. Qiao, and Y. Li, ‘‘Computer vision technology in agricultural automation—A review,’’ Inf. Process. Agricult., vol. 7, no. 1, pp. 1–19, 2020.
11. H. Tian, T. Wang, Y. Liu, X. Qiao, and Y. Li, ‘‘Computer vision technology in agricultural automation—A review,’’ Inf. Process. Agricult., vol. 7, no. 1, pp. 1–19, 2020.
12. A. Bharate and M. S. Shirdhonkar, ‘‘A review on plant disease detection using image processing,’’ in Proc. Int. Conf. Intell. Sustain. Syst. (ICISS), Dec. 2017, pp. 103–109.
13. P. Zhao, G. Liu, M. Li, and D. Li, ‘‘Management information system for apple diseases and insect pests based on GIS,’’ Nongye Gongcheng Xuebao/Trans. Chin. Soc. Agric. Eng., vol. 12, pp. 150–154, Jan. 2006.
14. G. Geetharamani and G. Pandian, ‘‘Identification of plant leaf diseases using a nine-layer deep convolutional neural network,’’ Comput. Electr. Eng., vol. 76, pp. 323–338, Jun. 2019.
15. E. M. F. El Houby, ‘‘A survey on applying machine learning techniques for management of diseases,’’ J. Appl. Biomed., vol. 16, no. 3, pp. 165–174, Aug. 2018.
16. C.-C. Yang, S. O. Prasher, P. Enright, C. Madramootoo, M. Burgess, P. K. Goel, and I. Callum, ‘‘Application of decision tree technology for image classification using remote sensing data,’’ Agricult. Syst., vol. 76, no. 3, pp. 1101–1117, Jun. 2003.

17. M. A. Ebrahimi, M. H. Khoshtaghaza, S. Minaei, and B. Jamshidi, ‘‘Vision-based pest detection based on SVM classification method,’’ Comput. Electron. Agricult., vol. 137, pp. 52–58, May 2017.
18. M. Sharif, M. A. Khan, Z. Iqbal, M. F. Azam, M. I. U. Lali, and M. Y. Javed, ‘‘Detection and classification of citrus diseases in agriculture based on optimized weighted segmentation and feature selection,’’ Comput. Electron. Agricult., vol. 150, pp. 220–234, Jul. 2018.
19. J. K. Patil and R. Kumar, ‘‘Analysis of content-based image retrieval for plant leaf diseases using color, shape and texture features,’’ Eng. Agric. Environ. Food, vol. 10, no. 2, pp. 69–78, Apr. 2017.
20. B. Sandika, S. Avil, S. Sanat, and P. Srinivasu, ‘‘Random forest based classification of diseases in grapes from images captured in uncontrolled environments,’’ in Proc. IEEE 13th Int. Conf. Signal Process. (ICSP), Nov. 2016, pp. 1775–1780.
21. A. Bharate and M. S. Shirdhonkar, ‘‘A review on plant disease detection using image processing,’’ in Proc. Int. Conf. Intell. Sustain. Syst. (ICISS), Dec. 2017, pp. 103–109.
22. P. Zhao, G. Liu, M. Li, and D. Li, ‘‘Management information system for apple diseases and insect pests based on GIS,’’ Nongye Gongcheng Xuebao/Trans. Chin. Soc. Agric. Eng., vol. 12, pp. 150–154, Jan. 2006.
23. G. Geetharamani and G. Pandian, ‘‘Identification of plant leaf diseases using a nine-layer deep convolutional neural network,’’ Comput. Electr. Eng., vol. 76, pp. 323–338, Jun. 2019.
24. E. M. F. El Houby, ‘‘A survey on applying machine learning techniques for management of diseases,’’ J. Appl. Biomed., vol. 16, no. 3, pp. 165–174, Aug. 2018.
25. C.-C. Yang, S. O. Prasher, P. Enright, C. Madramootoo, M. Burgess, P. K. Goel, and I. Callum, ‘‘Application of decision tree technology for image classification using remote sensing data,’’ Agricult. Syst., vol. 76, no. 3, pp. 1101–1117, Jun. 2003.
26. Mrs. Nikhat Fatima, Dr. Sameena Banu, “The Emerging of Deepfake Media and All-Inclusive Study of technological advances and Media Integrity Threat Challenge”, IOSR Journal of Computer Engineering (IOSR-JCE), p-ISSN: 2278-8727, Vol-25, Issue-4, August-2023, pp: 60-68, DOI: 10.9790/0661-2504026068.
27. Mrs. Nikhat Fatima, Dr. Sameena Banu, “Analysis on Splicing and Deepfakes in Viual Forgery and Image Fraud”, International Journal of Advance Research and Innovative Ideas in Education, (IJARIIE), UGC CARE, ISSN(O): 2395-4396, Vol-9, Issue-6, 2023, pp: 2712-2019.
28. Mrs. Nikhat Fatima, Dr. Sameena Banu, ”Attention-Guided Discrepancy Analysis for Robust Deepfake Detection”, YMER, Scopus, ISSN: 0044-0477, Vol-24, Issue-01 January-2025. Pp: 1018-1026.
29. Mrs. Rati D Joshi, Dr. Sameena Banu, “ Bio-Inspired Wire Sensor Network: A protocol for an Enhanced Hybrid Energy Optimization Routing”, Indonesian Journal of Electrical Engineering and Computer Science, Scopus Indexed, ISSN: 2502-4752, Vol-35 No. 3, September 2024, pp: 1808-1816, DOI: 10.11591/ijeecs.v35.i3.
30. Mrs. Rati D Joshi, Dr. Sameena Banu, “Swarm Intelligent Based Energy Optimization Protocol for Hybrid Routing in Wireless Sensor Networks”, International Journal of Engineering, Technology and Applied Research and Systems, Scopus Indexed, Vol-15, Issue-3, pp:23177-23182, June 2025, DOI: 10.48084/etasr.10550 .