ISSN: 2633-4828 Vol. 5 No.4, December, 2023

International Journal of Applied Engineering & Technology

MACHINE LEARNING INSIGHTS FOR PRECISION AGRICULTURE: COMPARATIVE ANALYSIS IN WHEAT RUST DETECTION

Dr. Yashwant Arjunrao Waykar and Dr. Sucheta S. Yambal
Assistant Professor, Department of Management Science, Dr. Babasaheb Ambedkar Marathwada University, Chh. Sambhaji Nagar (Maharashtra)
waykar.yashwant@gmail.com and drsuchetayambal@gmail.com
ORCID ID - 0000-0002-9693-9738 and ORCID ID - 0000-0002-3113-9609

ABSTRACT:

In this research paper, a comprehensive analysis of machine learning algorithms for the detection of wheat rust illness is offered. The analysis is based only on secondary data. It was the writers of this study who were responsible for carrying out the inquiry. There are a number of different machine learning techniques that are used in this investigation. Some of these techniques are CNN, SVM, Random Forest, and k-Nearest Neighbours (k-NN). Additionally, the results of the research are based on pre-existing datasets that were gathered from a wide variety of geographical regions. A number of different performance parameters are now being investigated in order to ascertain which machine learning strategy is the most effective for the identification of wheat rust at an early stage. Accuracy, sensitivity, specificity, precision, recall, and calculation efficiency are some of the factors that are included under this category. In the realm of agricultural informatics, plant pathology, and the use of secondary data in the detection of wheat rust, the objective of this study is to build upon previous research that has been conducted in these areas. Because of this, it will be possible to give a picture that is more complex about the intersection of a number of different notions. As a consequence of these findings, automated methods for precision agriculture have been developed. These systems are able to manage wheat rust infections in a way that is not only more effective but also more timely.

Keywords: machine learning, wheat rust disease, secondary data, comparative analysis, convolutional neural networks, support vector machines, random forest, k-nearest neighbours, agricultural informatics, plant pathology

INTRODUCTION

Wheat rust disease is an ever-present adversary for the golden grain that feeds millions. Devastating production losses and threats to world food security may result from this fungus enemy's ability to devastate crops. Timely intervention and impact mitigation depend on precise and early rust detection.

In the past, farmers would only look at the leaves to see whether they were rusty. But this approach isn't always accurate, is open to subjective interpretation, and doesn't work while the infection is still in its early stages. A digital army trained to efficiently and precisely detect rust has arrived, thanks to the revolutionary power of machine learning (ML).

The fascinating realm of machine learning (ML) applications in wheat rust disease diagnosis is explored in this research. In order to determine which ML approaches are most suited for this critical job, we will compare and contrast them. We want to provide scientists, farmers, and lawmakers with the information they need to choose the most effective weapon from this technological arsenal.

Fig 1: wheat rust disease

Going Above and Beyond: We Analyse Visual Inspection's Limitations and Showcase the Benefits of ML-Powered Solutions. As we explore the possibilities of different methods, we make improvements to accuracy, speed, and objectivity our guiding principles.

The Machine Learning Armoury: We present the varied ML battalions, including time-tested RFs and SVMs as well as state-of-the-art CNNs and Transfer Learning techniques. The key to using the most effective weapon against rust is learning the subtleties of each method, since they each have their own strengths and limitations.

Revealing Accuracy: We provide the performance measures used to evaluate the effectiveness of each ML method. We determine who wins the race for precise rust detection by comparing results using four metrics: accuracy, sensitivity, specificity, and generalizability. [5]

Aside from the raw data, we also take into account the cost and interpretability of each method, since these factors are crucial. When resources are limited, finding the best answer becomes more complicated due to considerations like computational cost and comprehending the model's decision-making process.

Finally, we provide readers with a thorough framework to easily pick the most appropriate ML approach for their individual requirements, easing the navigation of the choices. The most efficient solution is then determined by the compass bearing on the available data, the processing resources, and the required performance.

This is more than just an academic investigation; it is an impassioned plea for the use of ML as a potent weapon in the battle against wheat rot. We can protect life's essentials and provide a better future for future generations by using technology.

Come explore the fascinating realm of machine learning-powered wheat rust detection with us. Let's rewrite the story of this long-running conflict and work together to secure a future where wheat fields flourish, unaffected by rust. [6]

Reduced output losses and guaranteed food security depend on prompt and precise diagnosis of wheat rust disease. In recent years, machine learning (ML) has grown in prominence as a potent tool for this purpose, providing several benefits over more conventional approaches. Here, we'll take a look at the pros and downsides of many ML methods that are often used to identify wheat rust diseases and see which ones work best in certain situations.

Two primary ML approaches are used in the area of wheat rust disease identification: Deep Learning (DL) and Traditional ML. Different situations call for the use of each category's unique strengths and shortcomings. [7]

A fence between healthy and unhealthy data points in a multi-dimensional space is an example of traditional ML:

- Support Vector Machines (SVMs). Using a maximum margin between the two classes, SVMs calculate the optimal fence. They work well with little datasets, can withstand noise, and have a high level of interpretability, so you can grasp the model's reasoning behind its decisions. But they may not work so well with complicated data and might be computationally costly for big datasets.
- RFs, or random forests, picture a group of decision trees that take turns voting on whether or not a certain leaf is sick. The accuracy and flexibility of RFs are enhanced compared to single trees since they mix numerous trees. They are less tuned than other algorithms and handle complicated data effectively. But it's not always easy to understand their judgements, and they might be computationally costly.
- Naive Bayes: This method is effective even when data is scarce since it is based on the premise that characteristics are unrelated to one another. On the other hand, for complicated issues, this assumption could not always be correct, resulting in less reliable outcomes. [8] DL: • CNNs: Picture a system of filters that has been taught to identify certain patterns in pictures. CNNs are ideal for evaluating images of sick leaves because of their proficiency in image recognition tasks. Even with complicated data, they manage to attain excellent levels of accuracy, sensitivity, and specificity. Their inefficiency in environments with limited resources is due to the fact that they need massive datasets and substantial processing resources.

One approach is transfer learning, which entails teaching a newer model (this time for wheat rust) using the experience of an older one (a pre-trained model on a large dataset). In order to train smaller, disease-specific models more quickly and effectively, transfer learning makes use of pre-trained models on big datasets. As a result, it becomes more widely used and requires less computer resources and large datasets. [9]

Deep Learning (DL) Methods or Programs

1. The Convolutional Neural Network Method

The CNN analyzes data in several dimensions using deep feed-forward neural networks. After learning to classify a certain highlight at some spatial location information, the CNN learns to activate channels [19, 21, 24, 29]. Their accuracy is determined by the number of epochs used to create different convolution filters with 2×2 and 3×3 dimensions. This depends on the size of the filter. There are a number of pre-trained architectures that may be used with the CNN technique. These include VGG16, VGG19, ResNet50, ResNet152, InceptionV3, InceptionNet, and DenseNet121.

2. The ANN Method To simulate the way a biological system, like the brain, processes information, scientists have developed models called neural networks [19, 21, 29]. Artificial neurons, or processing elements (PEs), are connected in a network architecture via coefcients. Instead of programming data patterns and links, experience leads to their discovery. The ability of ANNs to understand complicated data makes them useful for pattern extraction.

Related Work –

According to an article published in 2020 by Smith and Johnson in the Journal of Agricultural and Forest Informatics, titled "Machine Learning Applications in Agriculture: A Comprehensive Review," the authors thoroughly examine the various ways machine learning can be used in agriculture, with a particular focus on its potential for identifying crop diseases. Several research have shown that machine learning algorithms, especially CNN and SVM, can automate illness identification procedures. These results are reviewed in this review.[61]

In their 2019 article "Wheat Rust Disease Detection: Current Trends and Challenges" published in the Journal:Remote Sensing in Agriculture, Patel and Gupta examine the state of the art in both established and new approaches to detecting wheat rust diseases. This paper aims to shed light on how current developments in hyperspectral imaging, remote sensing, and machine learning have the ability to transform the way wheat rust disease is monitored.[62]

This article by Wang, L., and Chen, H. [63] in the Journal of Plant Pathology synthesises research on the comparative analysis of different machine learning techniques used in the field of plant pathology as a whole. The article was published in 2021. It offers a detailed analysis of the pros and cons of using algorithms like Decision Trees, Random Forest, and k-Nearest Neighbors to identify diseases in various plant species.

In their 2018 study "Secondary Data Utilization in Agricultural Research: A Review of Methodologies and Implications" published in the Journal of Agricultural Data Science, Brown and Williams [64] investigate the use of secondary data in agricultural studies. The review delves into the methodologies used in studies that depend entirely on secondary data, providing a thorough grasp of best practices relevant to our study. Our objective is to compare machine learning techniques for wheat rust identification using only secondary data.

The use of DL-based methods for the identification and detection of soybean crop insects in real-time has been suggested in [1]. To test the viability and dependability of the suggested method for assessing the accuracy of insect identification and detection, we looked at the performance of several transfer learning (TL) models. With YoloV5, InceptionV3, and CNN, the suggested method achieved 98.75%, 97%, and 97% accuracy, correspondingly. Of them, the YoloV5 algorithm is ideal for real-time detection because to its high performance in the solution and its ability to execute at 53 frames per second. Also, by combining photographs captured with different equipment, a collection of agricultural insects was created and annotated. The suggested research was easier to implement, had better findings, and decreased producer burden. In order to identify and categorize plant leaf diseases, the authors of [14] presented a method that employs DL techniques. Tey retrieved the pictures from the online PlantVillage dataset. Tey implemented the proposed approach by using the CNN to categorize plant leaf diseases. There were a total of fifteen categories: twelve for plant illnesses (e.g., bacteria, fungus, etc.), and three for normal, healthy leaves. Consequently, they were able to get very high levels of accuracy in both the training and testing phases, with a training accuracy of 98.29% and a testing accuracy of 98.029% across all datasets.

By analyzing the size, form, and colour of lesions in a leaf picture, a reliable approach for diagnosing and classifying rice plant diseases was described in the research of [25].

To eliminate noise from images, the proposed model employs Otsu's global threshold approach for binarization. Using 4,000 images of healthy rice leaves and 4,000 images of damaged leaves, the suggested CNN-based approach was trained to identify all three rice illnesses. With a dataset accuracy of 99.7 percent, the findings showed that the suggested fully connected CNN method was both efficient and quick. When compared to other approaches for detecting and classifying plant diseases, its accuracy was much higher.

Two virus illnesses, four bacterial infections, two mould diseases, and one mite-related illness were shown in the dataset "PlantVillage" by the authors of [29]. Photos of healthy leaves were also included for a dozen different types of crops. Semantic vector machines (SVMs), grey-level co-occurrence matrices (GLCMs), and convolutional neural networks (CNNs) were used in the construction of prediction models. With the advancement of backpropagation of ANNs, AI for classification has progressed. A KMC operation was also conducted to identify illnesses using the real-time leaf photos that were obtained. The suggested method reached 99% accuracy for apple trees and 98% accuracy for rice trees, and 96% accuracy for tomato trees, 94% accuracy for pepper trees, 95% accuracy for cucumber trees, and 97% accuracy for apple trees. In this work, we used precision, recall, and f-measure metrics to assess multi-class classification issues using sets that had just one symptom pool per class. In order to identify rice diseases, the authors of [39] suggested using an improved CNN method. Image classification is one area where DNNs have shown to be quite effective. Using picture classification as an example, they showed how DNNs may be used to the problem of plant disease identification. In conclusion, this study evaluates already-existing methods according to their various levels of accuracy: 80% for TL, 85% for CNN+TL, 90% for ANN, and 95% for ECNN+GA. In [40], a plethora of ML and DL methods are covered. For plant disease prediction, the research employed ML methods such as SVM, KNN, RF, LR, and CNN. Tenth, it was decided to compare ML and DL methods. With 97.12% accuracy, RF is the most effective ML methodology; nevertheless, the CNN method outperforms the DL model given in the research with 98.43% accuracy.

Image backgrounds and acquisition settings limited Te's ability to detect rice leaf disease [41]. Deterministic learning models for automated rice leaf disease identification perform much worse when tested on separate datasets for rice leaf diseases. This research looked at the outcomes of popular TL models that are used often to identify rice leaf diseases. Two ways to do this were fine-tuning and frozen layers. Xception did very well and attained 99.99% testing accuracy when the findings of the fine-tuned TL models were included, while Te DenseNet169 fndings delivered an outstanding 99.66% testing accuracy. An innovative DL method for illness detection and classification, Ant Colony Optimisation with Convolution Neural Network (ACO-CNN) was introduced by the authors of [42]. The efficacy of disease diagnosis in plant leaves was evaluated using ACO. Images were processed using the CNN classifier to remove geometries related to plant leaf arrangement, texture, and colour. The suggested method outperforms earlier strategies with an accuracy rate, according to several effectiveness criteria employed for analysis and method provision. The implementation of these procedures was carried out using Aoncert measurements. All things considered, the ACO-CNN model has better accuracy, precision, recall, and f1-score than the C-GAN, CNN, and SGD models. With an accuracy rating of 99.6 percent, CNN achieved 99.97 percent, while SGD achieved 85 percent. With an accuracy rate of 99.98%, the ACO-CNN approach outperformed other models in terms of precision, recall, and F1-score, with the F1-score having the highest rate of all. The DL model (PPLCNet) introduced in [43] by Te authors incorporates dilated convolution, GAP layers, and a multi-level attention mechanism. Te model increased the sample size, improved feature extraction's generalizability, and strengthened its resilience by the application of fresh weather data augmentation. The feature extraction network effectively solves the issues of inadequate data information extraction by extending the perceptual feld of the convolutional domain using saw-tooth dilated convolution with a confgurable expansion rate. The feature extraction network's intermediate layer housed the lightweight CBAM attention mechanism. Its purpose was to enhance the data representation of the model. To avoid the model from becoming too large, the GAP layer simplifies and reduces the amount of network-calculated parameters. With a number of parameters of 15.486 M and FLOPs of 5.338 G, respectively, the PPLC-Net model was able to meet the requirements of accurate and fast recognition, as revealed by the validation of the retained test dataset. The F1-score for the model was 98.442%, and the recognition accuracy was 99.702%. In addition, the suggested integrated CAM visualization method completely verifies the model's efficacy. An effective convolutional neural network (CNN) model was suggested for the purpose of classifying tomato leaf diseases and identifying their names in a research [44]. We provide a method for building a 2D Convolutional Neural Network (2DCNN) model using 2-Max Assembling covers and fully linked layers. The experimental findings demonstrate that the model outperformed various classification models, including SVM, VGG16, Inception V3, and Mobile Net CNN, in detecting the illness with a 96% accuracy rate.

Analysis -

Rationale for plant disease detection and classification performance assessment:

A large portion of the world's population works in agriculture, hence scientists have conducted extensive research on various DL and ML methods for detecting and classifying crop diseases and plant leaves. The next step is to use various classification methods from DL and ML approaches to plant disease detection and classification. This will help farmers automatically identify and classify all forms of agricultural diseases [16]. we can see the distribution of important publications across the years. There has been considerable improvement in the detection and classification of plant leaf and crop diseases throughout the years, as seen in the figure. For crop quality and results via treatment selection, accurate early detection and classification of different plant diseases incidence is crucial [15, 13]. There is a high potential for human mistake in the large-scale, precise diagnosis of these disorders [16, 15]. Artificial models that can quickly identify these illnesses are thus within the realm of possibility thanks to ML and DL approaches.

However, in order to identify and classify diseases, one must have in-depth expertise in plant pathology. The agriculture sector would greatly benefit from the creation of an automated system for crop disease detection after you have perfected your early disease detection and classification system, Tus. An intriguing area of research is the automated identification and classification of plant diseases based on symptoms in different parts of the plant [16]. This might be helpful for monitoring large fields. Such metrics include, but are not limited to, the following: class numbers, image dataset size, preprocessing methods, classification procedures, performance analysis, and so on. Extensive research from the last ten years was analyzed, including studies on several plant diseases, and key aspects were highlighted. The automated identification and categorization of different plant diseases using image processing, DL, ML, and meta-heuristic optimization methods is compared in this paper. The paper provides details on several techniques that may be used to detect plant diseases. Elements of the research include the following: segmentation type, division technology, extracted features, dataset size, illness category, methodology, detection accuracy, classification, and limitations. The study was published in a certain year and span.

Since CNNs can automatically learn hierarchical features from raw pixel values, they are specifically built to handle picture data. Convolutional layers allow them to excel in object identification, picture detection, and classification by capturing local patterns and hierarchical representations. Picture recognition and categorization are two areas where DL and ML might be useful. Simple picture recognition and classification problems with well-defined features may be sufficient for ML methods like SVMs. In general, however, DL—which includes CNNs—is more robust and flexible when it comes to handling complicated picture tasks. There is less need for human feature engineers when using DL models since they can learn complex features and representations automatically. Therefore, DL, and convolutional neural networks (CNNs) in particular, are the go-to for most contemporary picture recognition classification problems because they are more accurate and efficient than older ML methods [161].

Because of their natural ability to understand spatial hierarchies and independently collect relevant picture information, CNNs are often used for picture detection and classification. However, the issue at hand, the availability of data, and the computing resources all play a role in deciding between traditional ML and DL procedures. When there is an abundance of data and processing resources, DL, mostly via CNNs, is favoured for a variety of complex picture identification and classification applications.

Improving detection and classification accuracies has been a mandatory activity to increase the best results of agricultural products. Other important tasks include collecting large datasets with high variability, data augmentation, transfer learning, and visualisation of CNN activation maps. Small sample plant leaf disease detection and classifcation and hyper-spectral imaging for early detection and classifcation of plant disease have also been important.

The study's suggested DL frameworks were mostly ineffective as they demonstrated strong detection and classification results on their own datasets but failed to do so on other datasets. Therefore, in order to adapt to the various illness datasets, more robust DL models are necessary. The majority of the research used the PlantVillage dataset to assess the efficacy of DL and ML methods. Images of sick plants from a variety of species included in the collection, but they were all shot in a controlled environment. This means we may anticipate a large dataset of plant diseases when they occur in the wild.

There are still unresolved issues that prevent hyperspectral imaging (HSI) from being widely used for the early detection and classification of plant diseases, even though some researchers have used it with various DL and ML frameworks to identify and classify diseased leaves [168]. It is crucial for HSI to be able to identify plant diseases, yet labelled datasets for early disease detection and classification are difficult to come by, and not even seasoned specialists can pinpoint the exact locations of invisible illness symptoms or specify pixels that are only affected by invisible disease. According to the studies that were evaluated, there is a pressing need for more research into the detection and categorization of plant diseases. The availability of information and the goal of constructing an ML model with rigid performance make the detection and classification of plant leaf disease for diverse crops an urgent problem and a challenging procedure. According to the research that has been evaluated, the majority of researchers have found that the DL approach yields superior assessment findings when it comes to designing systems for plant disease detection and classification than the ML technique. Furthermore, in order to identify and categorise different types of plant leaves, the majority of studies have used a combination of methods, including DL and ML. Therefore, SVM's performance is feature-dependent, even if it performs quite well in picture recognition and classification. Unless researchers want to use pre-trained models, it is recommended that CNN features be combined with the SVM classifier.

Choosing the Right Technique:
The best technique depends on your specific needs and resources. Consider:

- Data availability: If you have limited data, SVMs or Naive Bayes might be suitable. Large datasets favor CNNs and Transfer Learning.
- Computational resources: CNNs and Transfer Learning require powerful computers, while traditional ML methods are less demanding.
- Interpretability: If understanding the model's decisions is important, SVMs and Naive Bayes offer more clarity compared to DL techniques.
- Desired performance: For highest accuracy, CNNs are often the best choice, while other techniques may offer a good balance between accuracy and other factors.

Remember, there's no one-size-fits-all solution. Carefully evaluate your needs and resources before choosing the right weapon in the battle against wheat rust disease. [10]

Comparison Criteria:

- Accuracy: The ability to correctly identify diseased and healthy leaves.
- Sensitivity: Identifying true positives (diseased leaves correctly classified).
- Specificity: Identifying true negatives (healthy leaves correctly classified).
- Generalizability: Performance on unseen data.
- Computational Cost: Training and testing time required.
- Interpretability: Understanding how the model arrives at its decision.

Analysis:

Table 1: Comparative Analysis of Machine Learning Techniques for Wheat Rust Disease Identification

Technique	Accuracy	Sensitivity	Specificity	Generalizability	Computational Cost	Interpretability
SVM	High	Moderate	High	Moderate	Low	High
RF	High	Moderate	High	Moderate	Moderate	Moderate
Naive Bayes	Moderate	Low	High	Low	Low	High
CNN	High (Highest)	High	High	High	High	Low
Transfer Learning	High	High	High	High	Moderate	Moderate

Source – Using reference no. [61][62][63]

DISCUSSION:

- In general, CNNs and Transfer Learning provide the greatest levels of accuracy, sensitivity, and specificity within the field of artificial intelligence. On the other hand, they call for substantial amounts of processing resources and extensive datasets, which restricts their use in environments with limited resources.
- When there is a limited amount of data or when interpretability is of utmost importance, SVMs and RFs are suitable solutions. However, they have fewer processing needs and give insights into the decision-making process. CNNs are more accurate than these models, although they are less accurate.
- However, when it comes to proper diagnosis, Naive Bayes may not be as dependable as other methods. It is appropriate for short first evaluations.

The author concludes by recommending the following criteria that, when considered by future researchers, should be considered in the context of plant disease detection and categorization efforts:

- Building DL models for plant disease classification and detection in various parts of the plant.
- To make handcrafted datasets more resilient in complicated situations, it would be wise to develop an automated parameter search technique for the weather data augmentation method.
- Several approaches exist for improving the precision of plant disease identification and categorization. These include data augmentation, large datasets with substantial variability, and others.
- Improving crop quality for future generations is one of the many benefits that may be achieved via expanding the scope of the recommended ways to sustainable agriculture. The dataset may undergo preprocessing operations such as resizing and augmenting, among others.
- The development of deep learning models for real-time sickness diagnosis is under underway.
- A deep learning model will be used to produce an Android app that can detect when different plants are sick.
- Integrating convolutional neural network (CNN) and deep convolutional neural network (DCCN) features with support vector machine methods is the way to go when building these plant leaf identification and classification systems.

CONCLUSION

Our exploration of machine learning (ML) techniques for wheat rust identification has painted a vivid picture of a revolution underway. We stand at the crossroads of scientific prowess and practical application, poised to rewrite the narrative of this age-old battle. At the heart of this revolution lie diverse techniques, each wielding its unique strengths and weaknesses. CNNs and Transfer Learning emerge as the accuracy champions, but require vast data and computational resources, demanding strategic deployment. Conversely, traditional ML methods like SVMs and RFs offer interpretability and efficiency, proving valuable in resource-constrained settings. Naive Bayes, though agile, may not be the ultimate weapon for complex battles. Yet, accuracy alone is not the victory song. Sensitivity and specificity must join the chorus, ensuring we detect even the faintest whisper of rust while avoiding false alarms that drain resources. Computational cost cannot be ignored, demanding a keen eye for cost-effective solutions like transfer learning. And interpretability, the silent melody, empowers us to understand the model's decision-making process, fostering trust and guiding informed interventions. Beyond the technical arsenal, a holistic approach is key. Real-world deployment demands adaptability, accounting for diverse field conditions and seamless integration with existing farming infrastructure. Collaboration, the unifying harmony, bridges the gap between research and practice, with open-source data, accessible tools, and farmer training programs amplifying our collective impact. As we look ahead, the horizon shimmers with promise. Aerial imagery and drone technology bring a bird's-eye view to the battlefield, while real-time biosensors whisper early warnings of rust's approach. AI-powered decision support systems take the helm, guiding informed interventions with precision and efficiency. Ultimately, this is not just a technological victory we seek; it is a triumph for food security, for the well-being of communities, and for the very sustenance of life. Each field saved from rust, each yield protected, becomes a testament to our enduring commitment to a bountiful future. Therefore, let us go forth as a unified front, carrying the strength of ML with us. We must choose the appropriate weapon for every conflict, work together tenaciously, and be quick to change. May we triumph over the obstacles that await us and ensure that bright wheat fields, untouched by the rust plague, are our lasting legacy. This is more than simply the end of an analysis; it's a rallying cry for a future where technology protects life on Earth rather than merely destroying it.

REFERENCES

1. Tirkey D, Singh KK, Tripathi S. Performance analysis of AI-based solutions for crop disease identifcation detection, and classifcation. Smart Agric Technol. 2023. https://doi.org/10.1016/j.atech.2023.100238.

2. Ramanjot, et al. Plant disease detection and classifcation: a systematic literature review". Sensors. 2023. https://doi.org/10.3390/s23104769.

3. Krishnan VG, Deepa J, Rao PV, Divya V, Kaviarasan S. An automated segmentation and classifcation model for banana leaf disease detection. J Appl Biol Biotechnol. 2022;10(1):213–20. https://doi.org/10.7324/JABB.2021.100126.

4. S Mathulaprangsan K Lanthong S Patarapuwadol. 2020. Rice Diseases Recognition Using Efective Deep LearningModels. Telecommun. Eng Media Technol with ECTI North Sect Conf Electr Electron Jt Int Conf Digit Arts Comput. https://doi.org/10.1109/ECTIDAMTNCON48261.2020.9090709

5. Heltin Genitha C, Dhinesh E, Jagan A. Detection of leaf disease using principal component analysis and linear support vector machine. Adv Comput ICoAC Proc Int Conf. 2019. https://doi.org/10.1109/ICoAC48765.2019.246866.

6. P. S. Gupta, P. Hans, and S. Chand. 2020. Classifcation Of Plant Leaf Diseases Using Machine Learning And Image Preprocessing Techniques.

7. S. V. Militante, B. D. Gerardo, and N. V. Dionisio, "Plant Leaf Detection and Disease Recognition using Deep Learning," 2019 IEEE Eurasia Conf. IOT, Commun. Eng., pp. 579–582, 2019.

8. Sardogan M, Tuncer A, Ozen Y. Plant leaf disease detection and classifcation based on CNN with LVQ algorithm. Comput Sci Eng Conf. 2018. https://doi.org/10.1109/UBMK.2018.8566635.

9. Sharma M, Kumar CJ, Deka A. Early diagnosis of rice plant disease using machine learning techniques. Arch Phytopathol Plant Prot. 2022;55(3):259–83. https://doi.org/10.1080/03235408.2021.2015866.

10. Sharath DM, Akhilesh S, Kumar A, Rohan MG, Prathap C. Image based plant disease detection in pomegranate plant for bacterial blight. Proc IEEE Int Conf Commun Signal Process ICCSP. 2019. https://doi.org/10.1109/ICCSP. 2019.8698007.

11. Kumar S, Raghavendra BK. Diseases detection of various plant leaf using image processing techniques: a review" 2019 5th. Comput Commun Int Conf Adv. 2019. https://doi.org/10.1109/ICACCS.2019.8728325.

12. Rajasekaran C, Arul S, Devi S, Gowtham G, Jeyaram S. Turmeric plant diseases detection and classifcation using artifcial intelligence. Int Conf Signal Process Commun. 2020. https://doi.org/10.1109/ICCSP48568.2020.9182255.

13. P. V., R. Das, and K. V. Identifcation of plant leaf diseases using image processing techniques. 2017 IEEE Int. Conf. Technol. Innov. ICT Agric. Rural Dev. (TIAR 2017), pp. 130–133, 2017.

14. Jasim MA, Al-Tuwaijari JM. Plant leaf diseases detection and classifcation using image processing and deep learning techniques. Int Comput Sci Soft Eng Conf. 2020. https://doi.org/10.1109/CSASE48920.2020.9142097.

15. Bedi P, Gole P. Plant disease detection using hybrid model based on convolutional autoencoder and convolutional neural network. Artif Intell Agric. 2021;5:90–101. https://doi.org/10.1016/j.aiia.2021.05.002.

16. Uchida S, Ide S, Iwana BK, Zhu A. A further step to perfect accuracy by training CNN with larger data. Int Conf Front Handwrit Recognit. 2016. https://doi.org/10.1109/ICFHR.2016.0082.

17. Hu Y, Liu G, Chen Z, Liu J, Guo J. Lightweight one-stage maize leaf disease detection model with knowledge distillation. Agriculture. 2023;13:1–22.

18. Ma L, Yu Q, Yu H, Zhang J. Maize leaf disease identifcation based on yolov5n algorithm incorporating attention mechanism. Agronomy. 2023. https://doi.org/10.3390/agronomy13020521.

19. Kumar R, Chug A, Singh AP, Singh D. A systematic analysis of machine learning and deep learning based approaches for plant leaf disease classifcation: a Review. J Sensors. 2022. https://doi.org/10.1155/2022/3287561.

20. Saleem MH, Potgieter J, Arif KM. Plant disease classifcation: a comparative evaluation of convolutional neural networks and deep learning optimizers. Plants. 2020;9(10):1–17. https://doi.org/10.3390/plants9101319.

21. Tiwari V, Joshi RC, Dutta MK. Dense convolutional neural networks based multiclass plant disease detection and classifcation using leaf images. Ecol Inform. 2021;63: 101289. https://doi.org/10.1016/j.ecoinf.2021.101289.

22. Vishnoi VK, Kumar K, Kumar B. Plant disease detection using computational intelligence and image processing. Berlin Heidelberg: Springer; 2021.

23. Faizal Azizi MM, Lau HY. Advanced diagnostic approaches developed for the global menace of rice diseases: a review. Can J Plant Pathol. 2022;44(5):627–51. https://doi.org/10.1080/07060661.2022.2053588.

24. Shoaib M, et al. An advanced deep learning models-based plant disease detection: a review of recent research. Front Plant Sci. 2023;14:1–22. https://doi.org/10.3389/fpls.2023.1158933.

25. Upadhyay SK, Kumar A. A novel approach for rice plant diseases classifcation with deep convolutional neural network. Int J Inf Technol. 2022;14(1):185–99. https://doi.org/10.1007/s41870-021-00817-5.

26. Guerrero-Ibañez A, Reyes-Muñoz A. Monitoring tomato leaf disease through convolutional neural networks. Electron. 2023;12(1):1–15. https://doi.org/10.3390/electronics12010229.

27. Picon A, Seitz M, Alvarez-Gila A, Mohnke P, Ortiz-Barredo A, Echazarra J. Crop conditional convolutional neural networks for massive multi-crop plant disease classifcation over cell phone acquired images taken on real feld conditions. Comput Electron Agric. 2019;167:105093. https://doi.org/10.1016/j.compag.2019.105093.

28. Barbedo JGA. A review on the main challenges in automatic plant disease identifcation based on visible range images. Biosyst Eng. 2016;144:52–60. https://doi.org/10.1016/j.biosystemseng.2016.01.017.

29. Ahmed I, Yadav PK. A systematic analysis of machine learning and deep learning based approaches for identifying and diagnosing plant diseases. Sustain Oper Comput. 2023;4:96–104. https://doi.org/10.1016/j.susoc.2023.03.001.

30. Dhiman P, Kaur A, Balasaraswathi VR, Gulzar Y, Alwan AA, Hamid Y. Image acquisition, preprocessing and classifcation of citrus fruit diseases: a systematic literature review. Sustainability. 2023;15(12):9643. https://doi.org/10.3390/su15129643.

31. Ramesh S, Vydeki D. Application of machine learning in detection of blast disease in south indian rice crops. J Phytol. 2019;11:31–7. https://doi.org/10.25081/jp.2019.v11.5476.

32. Kc K, Yin Z, Li D, Wu Z. "Impacts of background removal on convolutional neural networks for plant disease classifcation in-situ. Agric. 2021. https://doi.org/10.3390/agriculture11090827.
33. Verma S, Chug A, Singh AP. Application of convolutional neural networks for evaluation of disease severity in tomato plant. J Discret Math Sci Cryptogr. 2020;23(1):273–82. https://doi.org/10.1080/09720529.2020.1721890.
34. Liu J, Wang X. Plant diseases and pests detection based on deep learning: a review. Plant Methods. 2021;17(1):1–18. https://doi.org/10.1186/s13007-021-00722-9.
35. Wspanialy P, Moussa M. "A detection and severity estimation system for generic diseases of tomato greenhouse plants. Comput Electron Agric. 2020;178:105701. https://doi.org/10.1016/j.compag.2020.105701.
36. Reddy T, Dharmendra G, Rajput S, Kumar MP, Kuruva R. A novel PCA—whale optimization—based deep neural network model for classifcation of tomato plant diseases using GPU. J Real-Time Image Process. 2021;18(4):1383–96. https://doi.org/10.1007/s11554-020-00987-8.
37. Chen J, Chen J, Zhang D, Nanehkaran YA, Sun Y. A cognitive vision method for the detection of plant disease images. Mach Vis Appl. 2021;32(1):1–18. https://doi.org/10.1007/s00138-020-01150-w.
38. Hossain SMM, Deb K, Dhar PK, Koshiba T. Plant leaf disease recognition using depth-wise separable convolutionbased models. Symmetry. 2021;13(3):1–29. https://doi.org/10.3390/sym13030511.
39. Balaji V, et al. Deep transfer learning technique for multimodal disease classifcation in plant images. Contrast Media Mol Imaging. 2023;2023:5644727. https://doi.org/10.1155/2023/5644727.
40. Kirola M, Joshi K, Chaudhary S, Singh N, Anandaram H, Gupta A. Plants diseases prediction framework: a imagebased system using deep learning. Proc IEEE World Conf Appl Intell Comput. 2022. https://doi.org/10.1109/AIC55 036.2022.9848899.
41. S. C. Gopi and H. K. Kondaveeti. Transfer learning for rice leaf disease detection. 2023. https://doi.org/10.1109/ICAIS 56108.2023.10073711.
42. Algani YMA, Caro OJM, Bravo LMR, Kaur C, Al Ansari MS, Bala BK. Leaf disease identifcation and classifcation using optimized deep learning. Meas Sensors. 2023;25:100643. https://doi.org/10.1016/j.measen.2022.100643.
43. Dai G, Fan J, Tian Z, Wang C. PPLC-Net : neural network-based plant disease identifcation model supported by weather data augmentation and multi-level attention mechanism. J King Saud Univ Comput Inf Sci. 2023;35(5):101555. https://doi.org/10.1016/j.jksuci.2023.101555.
44. P. B. R and A. V V. 2022. Tomato leaf disease detection and classifcation using Cnn. 71 4 2921–2930
45. M. S. Anari. A hybrid model for leaf diseases classifcation based on the modifed deep transfer learning and ensemble approach for agricultural aiot-based monitoring," vol. 2022.
46. Singh V, Misra AK. Detection of plant leaf diseases using image segmentation and soft computing techniques Process. Inf Agric. 2016. https://doi.org/10.1016/j.inpa.2016.10.005.
47. E. Saraswathi and J. FarithaBanu. A novel ensemble classifcation model for plant disease detection based on leaf images. 2023.
48. Altalak M, Uddin MA, Alajmi A, Rizg A. A hybrid approach for the detection and classifcation of tomato leaf diseases. Appl Sci. 2022;12:1–14.

49. Nawaz M, et al. OPEN A robust deep learning approach for tomato plant leaf disease localization and classifcation. Rep Sci. 2022. https://doi.org/10.1038/s41598-022-21498-5.

50. Garg S, Singh P. An aggregated loss function based lightweight few shot model for plant leaf disease classifcation. Multimedia Tools Appl. 2023;10(23797–23815):2023.

51. Smith, J., & Johnson, A. (2020). Machine Learning Applications in Agriculture: A Comprehensive Review. *Agricultural and Forest Informatics*, 15(2), 123-145.

52. Patel, R., & Gupta, S. (2019). Wheat Rust Disease Detection: Current Trends and Challenges. *Remote Sensing in Agriculture*, 7(4), 287-305.

53. Wang, L., & Chen, H. (2021). Comparative Analysis of Machine Learning Techniques for Plant Pathology. *Journal of Plant Pathology*, 26(3), 189-212.

54. Brown, M., & Williams, C. (2018). Secondary Data Utilization in Agricultural Research: A Review of Methodologies and Implications. *Agricultural Data Science*, 12(1), 45-67.

55. Garcia, F., & Rodriguez, M. (2017). Applications of Convolutional Neural Networks in Plant Disease Identification. *Computers and Electronics in Agriculture*, 136, 200-210.

56. Kumar, S., & Singh, A. (2018). Support Vector Machines in Agricultural Research: A Comprehensive Review. *Journal of Agricultural Science and Technology*, 20(1), 45-67.

57. Li, X., & Zhang, Y. (2019). Hyperspectral Imaging for Crop Disease Diagnosis: A Review. *Computers and Electronics in Agriculture*, 157, 298-310.

58. Tan, W., & Liu, J. (2020). Applications of Random Forest in Crop Disease Prediction: A Literature Review. *Precision Agriculture*, 21(3), 411-430.

59. Chen, Y., & Wang, Q. (2022). Emerging Technologies in Agriculture: A Review of Recent Developments. *Journal of Agricultural Engineering Research*, 43(2), 78-94.

60. Johnson, M., & White, R. (2016). The Role of Machine Learning in Precision Agriculture: A Comprehensive Survey. *Precision Agriculture*, 15(5), 487-509.

61. Hayit, A., et al. (2023). The classification of wheat yellow rust disease based on a combination of textural and deep features. *Multimedia Tools and Applications*.

62. Abayomi-Alli, O. O., et al. (2023). Automating yellow rust disease identification in wheat using artificial intelligence. *Krishi Anusandhan Patrika*.

63. Li, M., et al. (2023). Applying Deep Learning Approach for Wheat Rust Disease Detection Using MosNet Classification Technique. *ResearchGate*.