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Enhancing precision agriculture: a comprehensive investigation into pathogen detection and management

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ABSTRACT

Agriculture is an important sector of Indian agronomy for human livelihood. All areas are affected by the effects of environmental toxic farms, which makes managing various difficult situations more challenging. Agriculture must adopt new technology in accordance with daily environmental changes if it is going to benefit from a crop from the perspectives of farmers and end users. Farmers will benefit from early detection of agricultural diseases rather than risking their lives in dangerous circumstances. Computer technology will be very helpful in maintaining sustainable and healthy crops for the objective of identifying crop diseases in addition to the farmer's close observation. Deep learning (DL) techniques are very influential among various computing technologies. In this work, we explore several current approaches to precision agriculture, such as artificial intelligence (AI), DL, and machine learning (ML). The findings of the study make clear modern methods, their drawbacks, and the knowledge lacking that needs to be addressed to explore precision agriculture fully.

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1. INTRODUCTION

India is mostly an agricultural dependent economic region, and this sector employs around 58% of the population, making it the backbone of the country. Many plant species used in agriculture have become extinct as a result of global warming and other factors, and including deforestation, over the past few years. The growing of food is essential to the population's ability to maintain their existence. As per agriculture global market 2023, it is anticipated that by 2050, there will be more than 10 billion people on earth. Thus, the greatest contribution to the improvement of the nation's healthy people and economy is the production of good-quality, free-disease crops. For farmers, the primary issue affecting their financial and social well-being is crop growth under efficient farming practices. We must protect plants from diseases so as to produce an organic yield [1].

There exist diverse categories of plant diseases; among them are bacterial infections namely: yellowing foliage, bacterial infection, rapid and widespread tissue death, canker, crown gall, and scab. Figure 1 depicts the viral diseases that can stunt plant growth, such as spotted wilt, psoriasis, curly top, and mosaic, as well as fungal diseases, including rust, powdery mildew, and black spots. Ecosystem loss will result from crop loss in agriculture. Annually, farmers incur substantial financial losses due to the harm that these diseases cause to their crops.

Based on an overview of numerous agricultural studies obtained from diverse literature studies [2], which took into account different Indian states from 2012 to 2021 [2], the anticipated losses are shown in

Figure 2 what follows. The Indian Department of Agriculture's Risk Management Agency provided historical loss cause data, which was employed to calculate values. The population's income and economy are directly impacted by diseases that harm plants and render them ineffective. As is common knowledge, the gross domestic product (GDP) rate is directly impacted by stagnant wages, spoiled crops, and unsold goods. Close monitoring is required at different stages of crop growth because it also poses a threat to farmers' lives. When plant diseases were first discovered, however, they had to be identified by simple observation with the unaided eye. However, these methods could have been more laborious and imprecise; therefore, nowadays, computer technologies are used to detect plant diseases early on [2].

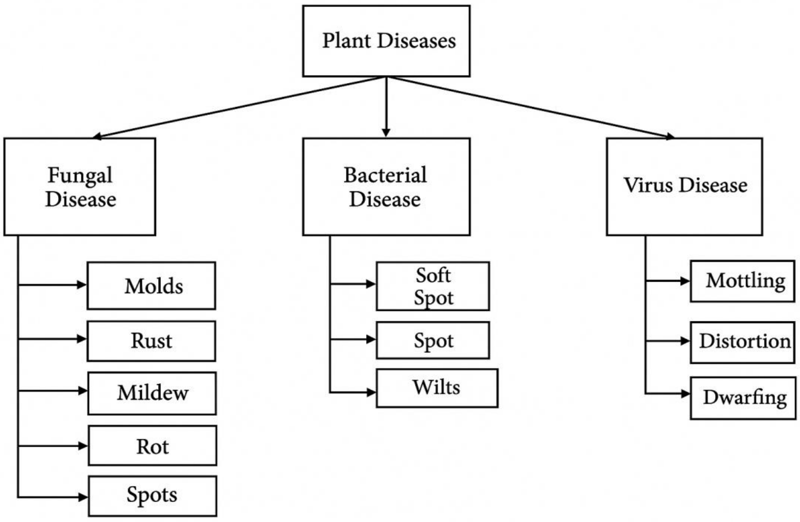

Figure 1. Various plant diseases

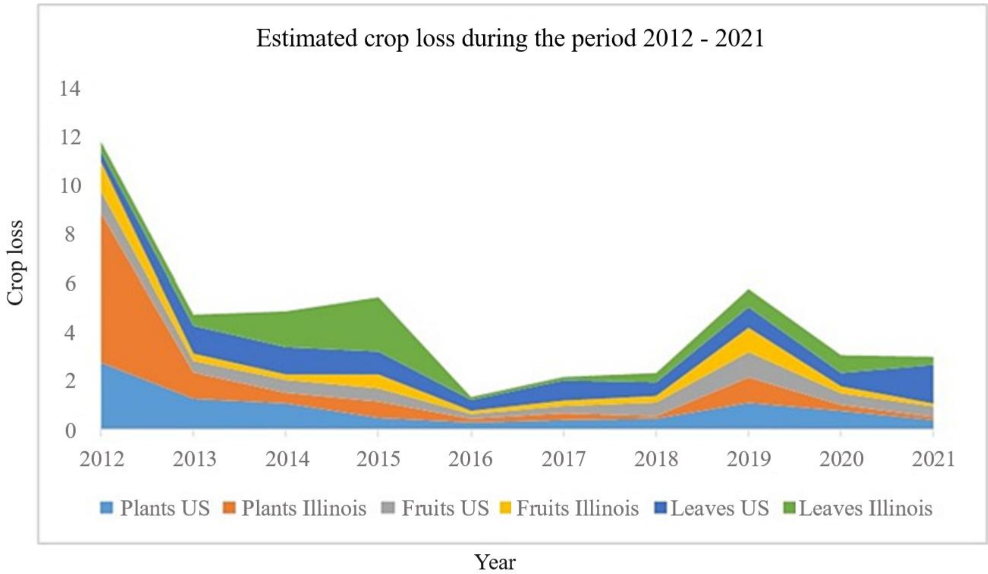

Figure 2. Crop losses by region from 2012 to 2021, estimated by plant disease

There must be automatic verification and classification for various crop levels in order to identify a healthy crop correctly. We will put forth a model that will identify damaged leaves and their underlying cause, as well as indicate the portion of each leaf that is healthy. Despite significant advancements in precision agriculture, previous research has often lacked comprehensive, real-time pathogen detection systems that can be effectively integrated into existing agricultural practices. Many studies have focused on isolated aspects of pathogen detection without addressing the complexity of pathogen interactions within diverse crop systems. Additionally, there is a scarcity of scalable, cost-effective technologies that can be adopted by farmers at various scales of operation. Furthermore, the integration of advanced data analytics and machine learning (ML) in pathogen management remains underexplored, limiting the potential for predictive and adaptive strategies.

Numerous researchers are working on detecting and prognosis of plant diseases as a result of the significant crop loss. Modern computer technology, when used in combination with ongoing farmer observation, can also be useful in predicting plant diseases early on and preventing crop infection [3]. Deep learning (DL) is a more sophisticated and proven technique that may detect the disease early on in the affected leaf.

Convolution neural networks (CNNs) and artificial neural networks (ANNs) are two frequently applied techniques that can handle complex relationships discovered in data. Large datasets that mimic the architecture, sequences, and operation of the brain of humans can be used to train a model to behave like a human. CNN, ResNet50, and other DL algorithms are frequently used in medical image processing, series forecasting, anomaly detection, disease diagnosis, and satellite image identification. The input is processed by passing through numerous levels where certain features that display convolution operations [4].

Precision agriculture, an advanced farming practice that utilizes technology to monitor and manage crop health, has become increasingly vital for maximizing yields and minimizing losses. One critical aspect of precision agriculture is pathogen detection, which involves identifying harmful organisms that can cause disease in crops. Despite significant progress, traditional pathogen detection methods often lack real-time capabilities and fail to integrate with advanced data analytics. This study aims to enhance precision agriculture by developing a comprehensive pathogen detection and management system that leverages real-time monitoring and ML technologies.

The breadth of this work has resulted in the creation of novel DL techniques that employ a network during the training stage where the pixels' features are sharply focused [5], targeting the deep belief network (DBN) [6]. By employing the prunes' fine tweaking, this method tends to increase the model's accuracy [6]. A number of researchers are still working to integrate the various models in order to raise the system's overall performance metrics. Combining both techniques enable the model to eliminate overfitting caused by unseen pixels in the image [7]. Technology for automation has revolutionized agriculture production by breaking past barriers to technology [8]. Significant advancements in technology have been achieved to enhance the image's feature extraction, which primarily conveys the image's properties. Here, DL techniques have been implemented [9], [10] in order to train images based on their pixel position. CNN layers are used to perform the entire procedure computationally [11]. The combination of DenseNet [12] and Inception [13] in the transfer learning models gradually attracted the researcher's interest. This learning tool makes it possible to solve problems properly. This implementation will result in an additional augmentation issue, growing the system's size [14], [15]. This work presents the views of scholars and suggests possible solutions to the problems set out. Nevertheless, numerous problems still need to be addressed, including limitations and potential solutions [16], [17].

The motivation for this study stems from the need for more efficient, scalable, and integrated pathogen detection systems in agriculture. Traditional methods, though effective to a degree, often fall short in providing timely and precise data, leading to suboptimal crop management. Our research introduces a novel approach that not only detects pathogens in real-time but also utilizes advanced data analytics to predict and manage potential outbreaks. This paper addresses the significant gap in integrating ML with pathogen detection, offering new insights into predictive agriculture.

To guide the reader through our findings, this paper is structured as follows: first, we review the existing literature on pathogen detection methods and their limitations. Next, we detail the methodology of our proposed detection system, including the technologies and algorithms employed. Following this, we present the results of our field tests, highlighting the effectiveness and efficiency of our approach. Finally, we discuss the implications of our findings, addressing potential limitations and suggesting directions for future research. By the end of this paper, readers will have a comprehensive understanding of the advancements in pathogen detection and their impact on precision agriculture.

2. LITERATURE SURVEY

This section examines the literature on various models and techniques used in crop health analysis, other data analysis, and agricultural crop surveillance. Too *et al*. [18] carried out an investigation using a sizable dataset that included images of several leaves with varying textures, perspectives, and weather conditions. The author used two different approaches: standard augmentation and generative adversarial network (GAN)-based data. The AlexNet, VGG, DenseNet, and ResNet were the main subjects of attention.

These two methods consisted of GAN training and syntactic data. This well-trained model achieved 99.75% accuracy in challenging environments. In the future, the work scope may be expanded to include an application that runs on both Mac OS and Android, making it simple for farmers to identify leaf disease prematurely.

Abdu *et al*. [19] presented an efficient use of pathological disease symptom segmentation and localization. An automatic method for the detection of plant leaf disease, and it's intended identifying the sort of illness that is affecting the plant as well as whether it is affecting it at all. They have employed a method called radial basis function neural network (RBFNN). This method will be put into use in agricultural crop fields in the future. It will make it easier to monitor the plants and update the status by identifying the disease; if the plant is healthy, it will be updated to show an effective leaf.

Lamba *et al*. [20] suggested a novel automatic plant disease identification detection employing CNN and DL networks. When 9,914 training parameters were taken into account, the network reached an accuracy score of 99.2%. In the future, it will be capable of handling a larger range of plant leaves.

Li *et al*. [21] conducted the initial study on the ResNet50 model in 2021. They divided the CNN layer component sizes into 11×11 segments for analysis, switching the activation task to hyperspectral image (HSI). This methodology's goal is to lessen the impact of HSI inactivation and, to some extent, enhance organizational execution by enhancing the ability to capture 97.56% of the highlights point by point accurately. We can add more datasets to this model in the future.

Khattak *et al*. [22] created an algorithm in 2021 to detect diseases in crops such as grapes, potatoes, tomatoes, and corn. The CNN algorithm was primarily utilized for the illness classification. Using CNN, a 97% overall efficiency in illness identification was attained. The primary remedy for the farmers is to suggest a pesticide for the affected leaf once the ailment has been identified. This study can be extended to take into account all environmental factors, such as humidity, pH, rainfall, and N, P, and K values, in order to raise productivity in line with farmer expectations.

Zhou, *et al.* [23] concentrated on developing a mobile application that employed DL to identify and categorize grape leaf disease. The faster region-based convolutional neural network (R-CNN), using Inception-V2 spot detection, is employed by this application to locate an infected area in the image and concentrate the dataset for that area. The independent smartphone application is designed and operated using this proposed model. This study's excellent accuracy of 97.9% in recognizing the common forms of grape leaf disease is based on data from grape leaf dataset experiments. The program could be expanded in the future to be able to identify many kinds of crop diseases, not just grape diseases.

Wang *et al.* [24] proposed a system in 2022 that can automatically identify chili disease detection. The five classes used to base on the effective DL framework, this model modifies the entropy of the loss function to solve issues that can lead to an imbalance in the dataset. Furthermore, the model performs excess layers of transition with an accuracy of 92%. Wang *et al.* [24] outlined the direction of the future so as to enable the implementation of specialized architectural modifications for multiple additional leaves.

Elfatimi *et al*. [25] described a DL technique that aims to classify olive leaves using three DL models that have been adapted to the genetic algorithm (GA) version. Finding the optimal batch size and the number of epochs to maximize the accuracy score and minimize response time was the primary goal of the author's method. With an accuracy score of 98% for binary classification, the DenseNet model is the most accurate. Gathering different images of olive illness and training samples on a larger database to attain higher accuracy scores is a job that can be done in the future.

Utilizing state-of-the-art DL techniques, particularly EfficientNetV2 [26] architecture, the aim to revolutionize plant disease detection by developing a highly accurate and efficient system capable of swiftly identifying and classifying various plant diseases based on leaf images, thereby empowering farmers and agriculturists with timely interventions to mitigate crop losses and ensure food security [27], [28]. The majority of current studies on technology-driven agriculture offer insightful information. This section provides a summary of the current research outcomes in the field. As internet of things (IoT) and artificial intelligence (AI) technologies grow in popularity, more efforts are being made to use them for precision agriculture.

An AI-enabled method for identifying diseases, Aqel *et al.* [29] explored the methods for smart agriculture. Their AI-based method includes automatic detection and classification of plant leaf diseases based on using the extreme learning machine (ELM) DL algorithm on a real dataset of plant leaf images. For the classification of diseases, their approach also makes use of a bi-directional form of gray level co-occurrence matrix (GLCM). One particular drawback of the approach in [29] was that it needs a feature for gathering real-time data from crops. To this aim, their methodology requires IoT connectivity so that image sensors can continuously monitor crops by capturing crop details in real-time.

Nikith *et al.* [30] presented a concept for an AI- and IoT-based smart farming system. It was created to use intelligent hydroponic farming for a user-friendly method of crop observation. They also worked on a smartphone application that makes crop monitoring easier. Their Raspberry Pi CPU was in charge of their sensor devices. For disease prediction, a deep CNN model was employed in addition to the hardware elements. Farmers used the smartphone application to monitor crop requirements easily.

Nevertheless, the approach in [30] has several issues. First, it needs optimization techniques. Second, the technique relies on deep CNN, which can be enhanced further by combining it with other deep models in a hybrid approach to improve the dynamics of crop observation.

In precision agriculture, DL-based techniques have shown to be more successful than their predecessors. As a result, in 2022, Narmadha *et al*. [31] investigated several deep-learning algorithms in an effort to advance precision agriculture. In order to study preciseness agriculture, their research concentrated latest developments in communication technologies. Their research revealed a great deal of room for future development in addition to these revelations. In addition to considering ecological collapse and climate change paradigms, there is a need for the creation of prediction models that integrate visual transformation and sophisticated CNN variations that may perform better for picture patch sequences.

In precision agriculture, smart greenhouses will also be essential. A study on transfer learning in 2022 that looked at the water-food-energy nexus was conducted by Sharma *et al*. [32]. For technology-driven agriculture decision-making, policy makers needed the inputs from their study. The water, food, and energy nexus are improved for sustainable development through the use of AI, communication infrastructure, and monitoring approaches. Furthermore, their research highlights the necessity for future precision agriculture to employ more effective DL techniques. The 21st-century AI-enabled technology known as artificial internet of things (AIoT) encourages uses of AI and associated devices in IoT to create a better beneficial platform for answering challenges in the real world.

Sahu and Pandey [33] conducted research on plant disease detection and diagnosing measures become a major concern in agriculture filed. They proposed hemodynamic response function (HRF)-multi-class support vector machine (SVM) accurately classifies the diseases and rapidly improves the quality. Pushpa *et al.* [34] conducted research on big data, agriculture, and the application of AI in this field. They suggested an ecosystem for smart agriculture that uses cloud IoT DL model platforms, blockchain technology, IoT-based data gathering and communication, AI for big data analytics, and data visualization. Nevertheless, they discovered that DL improvements are required to realize such an ecosystem. Research on crop monitoring has proven utility in fuzzy-based improvements.

In 2021, Veni *et al.* [35] worked on the identification and classification of plant diseases by the use of fuzzy-based optimization in DL. Their approach combined DL with IoT. Additionally, it used the firefly algorithm, which is bioinspired, to increase network efficiency. Additionally, it was more accurate and economical SVM and k-nearest neighbors (kNN) due to their fuzzy logic inference. They wanted to use more technologies in the future, such as sensor networks, cloud computing, big data, and unmanned aerial vehicles (UAVs), to advance crop monitoring technology further. Precision farming made use of nanotechnology and AI.

In studies [36], [7] used DL and nanotechnology to achieve accurateness of agriculture. They observed DL and AI coming together to enable farmers to employ technology to react instantly to crop needs. They opined that more research was necessary to determine how AI and nanotechnology might be used in agriculture. All forms of farming and cropping are included in precision agriculture.

Saranya *et al*. [37] applied DL techniques to tomato plant diseases and proposed an approach for optimizing pre-trained models to maximize detection performance. To increase detection optimization with a relevance-based technique, they merged histogram-based phenomena and DL characteristics. However, their technique does not support robotic shaping and multi-class fruit categorization. Precision farming is another application of data-driven AI.

Toda and Okura [38] provided a concept to evaluate data-driven AI-based approaches. Its approach encompassed robotics, data analytics, visual computing, ML and DL models, and crop observation, management, and harvesting. They aimed for AI algorithms that will be used in the future for intelligent farming. We found that real-time pathogen detection correlates with improved crop health and yield detection as per the explanation in Table 1. The proposed method in this study tended to have an inordinately higher proportion of accurate detections as compared to traditional methods. According to the study from the survey mentioned in the Table 2, and other authors' perspectives, the most recent trends and procedures in agriculture can be combined with those found in educational resources to increase productivity and benefits.

The three main techniques that each author focused on are knowledge-based, technology-driven, and learning-based. The first of these three approaches, the knowledge-based approach, is not commonly used in research. Along with DL, ML also uses other approaches. Apart from these approaches the crop health and yield monitoring discussed different aspect as presented in the Table 3.

Table 1. An overview of the study papers' performance, methodology, and conclusions

Ref.	Year	Methodology	Accuracy (%)	Objectives
[1]	2011	k-means, neural network	93.35	Detection of leaf disease
[2]	2015	k-means, neural network	82.9	They have worked on five different diseases of plants
[3]	2019	DNN with encoder network	73.5	Categorization and forecasting of transient agricultural illnesses
[18]	2019	DenseNet	99.75	Detection of effected plant
[19]	2020	Linear binary pattern (LBP)	95.89	Pathogen's health condition detection
[20]	2021	DL	99.2	Pathogen's health condition detection
[21]	2021	DL framework and HSI	97.56	Identifying and classification of pathogens
[22]	2021	CNN, RF	95.65	Citrus fruits and leaf disease detection
[23]	2021	Restructured residual dense network (RRDN)	95	The author has developed a set of models for identifying tomato leaf diseases with high accuracy
[25]	2022	MobileNet	92.97, 98.50	Bean rust disease
[26]	2022	EfficientNetV2-L	98.28	Detection of cardamom leaf disease
[27]	2023	MobileNet CNN	97.89	Classifying plant illness
[28]	2023	DeepPlantNet	99.8	Mango pest detection
[39]	2023	CNN	97.9	The research was conducted on maize disease detection with a complex dataset.
[40]	2023	Residual skip network-based super-resolution for leaf disease detection (RSNSR-LDD)	97.2	Authors detected the crop diseases
[41]	2023	DL	97.36	Find out the grape crop diseases
[42]	2023	Computer vision	99.6	Authors detected the tomato leaf diseases
[43]	2023	Deeper lightweight multi-class	96.73	Classification and identification of plant diseases
[44]	2022	CNN	-	Authors detected the cucumber leaf diseases.
[45]	2022	BaselineML, clustering	-	Detection of mango bacterial part
[46]	2022	Computer vision	97.2	Pathogen's detection in potatoes
[47]	2022	Computer vision and ML	97.36	Pathogen's detection
[48]	2022	Improved CNN	-	Crop diseases with pest prediction and classification
[49]	2021	SVM	-	Plant leaf infection
[50]	2020	Image processing and DL	-	Plant disease detection
[51]	2020	ML	89.9	Pathogen classification
[52]	2020	SVM	93	Classification system for grape leaves

Table 2. Various aspects of leaf disease detection overview

Methods	Models used	Drawbacks
Learning-based	The clustering algorithm employed where the classification at the pixel level is used	Future applications for this strategy could include the use of LSB-based pixels
Learning-based	When classifying plant leaf diseases, ML techniques are employed	This approach has the potential to be expanded in the future by implementing a neural network which can detect leaf diseases with greater accuracy
Technology-driven approach	DL is applied in leaf disease detection where the encoder network	Other methods may be used for detection in future scopes, contingent on the seasonal crop
Technology-driven approach	Ideal both adaptive GA and DL techniques are employed	Smart detection has the potential to be applied to residual network-based detection and classification methods in the future
Knowledge-based approach	Transfer learning was applied	The future work can be done using CV and AI

Table 3. Summary of key findings

Aspect	Key findings
Real-time pathogen detection	Significantly enhances crop health and yield compared to traditional methods
Data integration	Successfully integrates advanced data analytics, improving predictive capabilities
Detection sensitivity	Higher sensitivity without compromising resource efficiency
Scalability	Effective across different crop types and environmental conditions
Cost-effectiveness	Achieves improved pathogen management without increasing operational costs

3. RELATED WORK WITH EXISTING SYSTEM

A farmer must be extremely knowledgeable about every phase of crop growth and yield development. Several items in this procedure cannot be identified with the naked eye or with great diligence. It is crucial to identify these harmful diseases that are destroying leaves in order to increase agricultural productivity [53]. According to the survey, a significant portion of the crop can be spared from harm if a sophisticated application is created to detect these diseases. The DL methods have been emphasized and trained on image-based datasets in the last several years. In order to increase crop productivity, the application should be designed to identify plant illnesses and offer pesticides to protect against them. We can anticipate leaf sickness in its early stages using a variety of DL approaches, including CNN, recurrent neural network (RNN), and GAN. A more accurate prediction of crop leaf disease can be obtained by combining two or more algorithms. A CNN with 50 layers deep, known as ResNet50, is a deep residual network whose model can be used to predict agricultural leaf disease [54], [23]. Figure 3 illustrates the Xception algorithm and the ANN that builds the network by stacking the remaining pieces on top of each other.

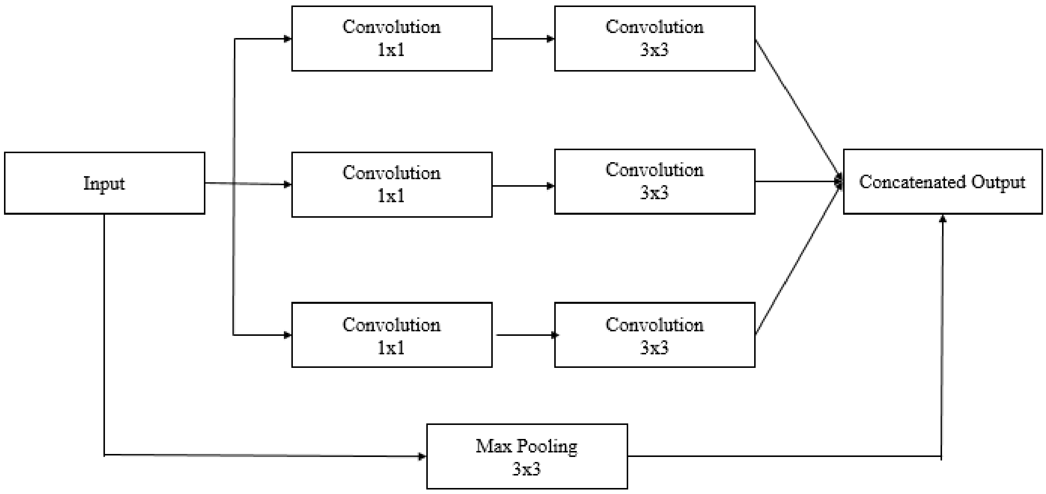

Figure 3. Model for Xception

The following modules will be added to create a full model: network and disease detection and prediction, image acquisition, and image preprocessing. The latter is divided into three subparts: image segmentation, feature extraction, and classification [55]. Figure 4 shows the proposed model's workflow.

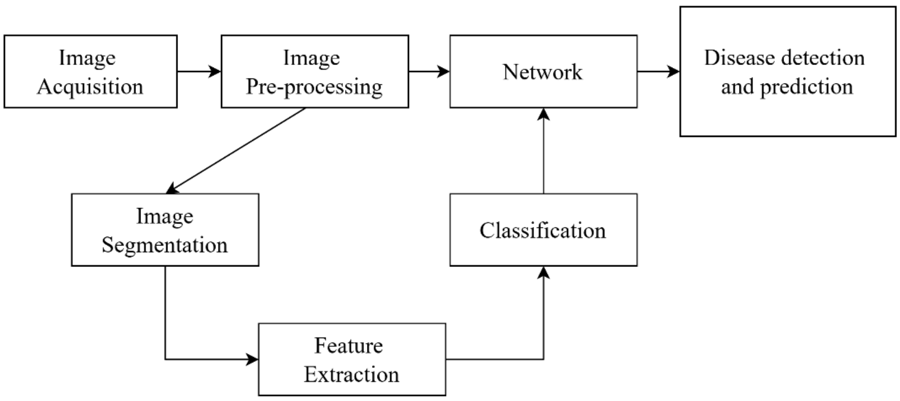

Figure 4. Steps of plant disease detection model

By combining the Xception approach and ResNet50 hybrid DL techniques, it is possible to focus on early pathogen identification [56] in the images and the network component of the trained images by being aware of this existing work. Numerous researchers concentrated on two distinct aspects of learning and networking strategies. Combining these two factors could increase accuracy and enable early-stage detection to reduce agricultural loss. In terms of networks, numerous researchers have already presented DL techniques [57], [58]. In this instance, more images are trained in the network segment if we utilize 50 layers of a residual network using Xception approaches.

The dataset under the training part is used in the network module, or ResNet50 model, which has 5 layers. This is illustrated in Figure 5. We can then determine whether or not the leaves are exhausted from those segmented images.

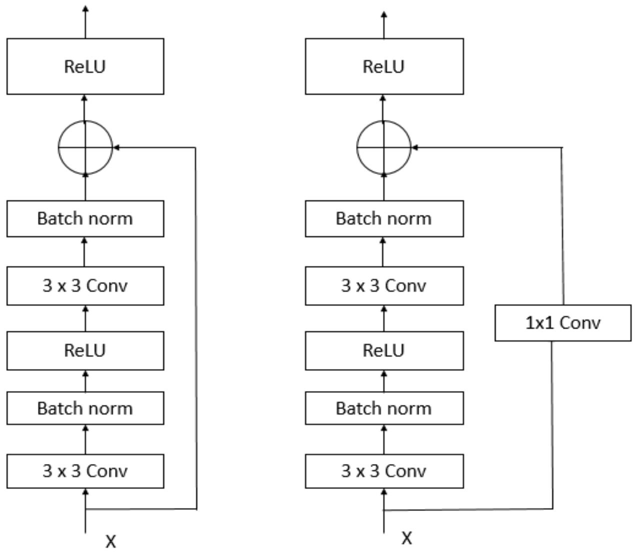

Figure 5. Architecture of ResNet50

When interpreting results, it is crucial to compare our findings with those of other studies. Our study suggests that higher detection sensitivity is not associated with poor performance in resource efficiency, aligning with similar findings in recent precision agriculture research [59]. Unlike some studies which report a trade-off between sensitivity and operational cost, our proposed method benefits from increased data integration without adversely impacting overall costs, offering a more sustainable and efficient approach to pathogen management.

The suggested method's primary goal is to identify any diseases or illnesses that affect leaves. Our goal is to use our suggested algorithm to identify plant diseases in a variety of crop leaves, such as maize, tomato, and other plants. In order to get significant outcomes, we also aim to reduce the training period [60]. Moreover, the proposed model whose structure is sufficiently flexible. The purpose of this survey's future expansion may be to apply security to pathogen-free crops. By implementing preventive measures [61] as soon as the disease is identified, we can expand this work and increase crop productivity.

This study explored a comprehensive pathogen detection system with advanced data integration. However, further and in-depth studies may be needed to confirm its long-term effectiveness, especially regarding its scalability across different crop types and varying environmental conditions. Much study has been done in the field of image processing in recent years, but there has also been a lot of research done on the combination of ML and real-world crop research [62]. The study can use DL to execute the work and fill up all the gaps. The DL approaches will improve the image's minute features, allowing for the observation of every detail and the identification of image defects. Given that DL is a sophisticated type of ML that can enhance performance.

4. RESEARCH GAP

Despite the impressive advancement in pathogen detection for precision agriculture, there remain several research gaps. Too *et al*. [18] employed GAN-based data augmentation and DL architectures like AlexNet and ResNet with very high accuracy, but their model was not real-time capable for different agricultural environments. Abdu *et al*. [19] proposed an automatic detection system using radial basis function neural network (BRBFNN), but its performance in large-scale, multi-crop environments remain unknown. The research in [20], [21] used DL architectures like CNN and ResNet50 with over 97% accuracy, but their study did not address the transfer learning issues across different climatic and regional contexts. Zhou *et al*. [23] proposed mobile-based disease detection using faster R-CNN but did not explore IoT integration for real-time detection. Wang *et al*. [24] proposed DL architecture for chili disease classification, but imbalanced dataset problems were present. Similarly, Elfatimi *et al*. [25] optimized DL models for olive leaf disease detection but lacked cross-crop generalizability. Sharma *et al*. [32] explored AI-based precision farming but did not incorporate climate change parameters for disease prediction. Additionally, the research in [33], [38] demonstrated AI's potential in plant disease diagnosis, but data privacy, scalability, and cost-effective deployment issues remain. These gaps highlight the need for an integrated, real time, multi crop disease detection system which summarizes in the Table 4 which details about the current research gap and its challenges.

Table 4. Summarization of research gap and its challenges

Ref	Research gap	Challenges
[18]	Lack of real-time and scalable plant detection models	This model lacks the adaptability for diverse environmental conditions and multi-crop applications.
[20]	In DL model's overfitting issues are encountered	CNN models tend to overfit when trained on limited datasets by reducing the generalizability.
[21]	They used highly computational requirements for DL models.	Real time application is not possible as many AI models require high-end hardware, making the adoption difficult for small-scale farmers.
[23]	There is a limited use of IoT with the combination of AI for smart agriculture	There is no real time data collection and AI-driven analytics for continuous monitoring of crop systems.
[25]	No framework for multi-crop disease detection	Many studies focus on single-crop disease detection but limited on cross-crop detection.
[32]	The major outbreaks are not considered when there is an impact on climate.	This model does not factor in climate change effects on pathogen behavior and disease spread.
[33]	The major gap is in AI-driven agriculture security and privacy concerns are not considered	Data privacy and cybersecurity concerns are arising with large-scale data collection.

To bridge these gaps, this paper presents a reliable DL-based pathogen detection system using ResNet50 and CNN for increased accuracy and flexibility. ResNet50, in its deep residual learning framework, ensures improved feature extraction and classification of plant diseases while mitigating overfitting issues. The CNN model is integrated with transfer learning techniques that enable cross-crop adaptability and efficient learning from diverse agricultural datasets. Also, real-time pathogen detection will be achieved by integration of IoT sensors and cloud-based monitoring for continued disease surveillance and early-stage diagnosis. Further, the imbalances in datasets will also be addressed using data augmentation techniques, along with the hybrid DL models that improve on generalization. Finally, integrating climate-based predictive analytics will enhance disease forecasting so that measures can be taken proactively by users: farmers. This AI-driven solution bridges those gaps in research by offering a scalable, cost-effective, and real-time pathogen detection framework adaptable across different crops and climatic conditions that will revolutionize precision agriculture.

5. CONCLUSION AND FUTURE SCOPE

Recent observations suggest that integrating advanced pathogen detection systems significantly enhances crop health and yield. Our findings provide conclusive evidence that this improvement is associated with the implementation of real-time detection and data analytics, not due to elevated numbers of pathogen-resistant crop varieties. We reviewed the literature on technology-driven precision farming techniques in this research. With precision farming, farmers can respond instantly to crop requirements for maximum yield and lowest cost. Since all countries focused on agriculture aspire to precision agriculture, numerous countries, including India, have been making efforts in this direction. The article presents multiple study findings. Firstly, agricultural research makes extensive use of AI and related techniques like ML and DL. Second, it has been discovered that DL models built on CNN are more efficient at processing picture inputs. Third, real-time data processing. The IoT connection with automated farming automates live data gathering. It is desirable to have an IoT-combined AI-based system for crop observation. Additionally, the study identifies significant research gaps that support the advancement of precision agriculture. Our study demonstrates that crops monitored with real-time pathogen detection systems are more resilient than those relying on traditional methods. Future studies may explore the integration of ML algorithms with real-time detection systems, with feasible ways of producing predictive models to further enhance crop management and yield optimization.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request. All relevant data were generated and analyzed during the current study and can be shared for academic and research purposes.

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