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A Comprehensive Review on Intelligent Techniques in Crop Pests and Diseases

K. Sai Susheel[1], R. Rajkumar[2*]
[1]School of Computer Science and Engineering
Vellore Institute of Technology
Vellore, Tamil Nadu, India
Kurrasai.susheel2020@vitstudent.ac.in
[2*]School of Computer Science and Engineering
Vellore Institute of Technology
Vellore, Tamil Nadu, India
Corresponding Author: rrajkumar@vit.ac.in

Abstract: Artificial intelligence (AI) has transformative potential in the agricultural sector, particularly in managing and preventing crop diseases and pest infestations. This review discusses the significance of early detection and precise diagnosis of various AI tools and techniques for disease identification, such as image processing, machine learning, and deep learning. It also addresses the challenges of AI implementation in agriculture, including data quality, costs, and ethical concerns. The analysis classifies the hurdles and AI offers benefits such as improved resource management, timely interventions, and enhanced productivity. Collaborative efforts are essential to harness AI's potential for sustainable and resilient agriculture.

Keywords: Artificial Intelligence, Agriculture, Disease Prevention, Pest Management, Early Detection, Precision Agriculture, Challenges, Sustainability.

I. INTRODUCTION

Despite playing a crucial role in maintaining global food security, agriculture faces ongoing difficulties due to crop diseases and insect infestations. These dangers can result in significant output losses, affecting farmers' livelihoods and food availability for an expanding population. The application of artificial intelligence (AI) in disease prevention and pest control has emerged as a viable remedy with game-changing potential in response to these difficulties. This study intends to look at the use of AI technology in the agricultural sector for managing and preventing crop diseases. A thorough literature study, in-depth background research, critical discussion, and practical recommendations are used to address the possibilities and difficulties of integrating AI-driven solutions in this essential industry. The analysis of the existing publications and research articles on AI applications in agriculture is part of the literature study. Here, it discusses the many AI approaches for crop disease detection, including image recognition, machine learning, and data-driven models. Understanding the context and significance of AI in preventing and managing agricultural diseases and pests is necessary for developing efficient techniques. In the background, research outlines the challenges farmers face in detecting and preventing crop diseases and problems.

It highlights how these issues influence the profitability of agricultural and food production and focuses on these issues' economic, social, and environmental effects. In this study, the exciting possibilities of AI technology are examined for managing pests and avoiding disease in the agriculture industry. By conducting a thorough literature review, background analysis, engaging in critical discussion, and making helpful ideas, the research aims to contribute to ongoing efforts to harness AI for sustainable and resilient agriculture. Crop protection will be efficiently optimized, production will rise, and food security will be bolstered to withstand the complexity of growing societal and environmental concerns.

II TOOLS AND TECHNIQUES USED IN THE DETECTION OF DISEASE AND PESTS IN CROPS

In this digital era, there are developed and developing various advanced tools and techniques for detecting diseases and pests in crops. Image processing technologies and methods that make use of the capabilities of computer vision and AI algorithms are used to identify diseases and problems in crop lines. These techniques are essential for recognizing and analyzing crop health and enabling prompt responses to stop additional harm. The developed tools and techniques are mentioned below with descriptions

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Table 1. Different Techniques in the Agriculture

Technique	Tool	Description
Image Processing and Preprocessing	PyTorch and OpenCV	Crop photos are enhanced, filtered, and preprocessed using image processing methods to make them more effective for spotting diseases and pests. Image scaling, noise reduction, color correction, and contrast enhancement are standard preprocessing techniques [1]. Through greater feature extraction and precise analysis, these procedures raise the general quality of photos [2].
Feature Extraction	"Autoencoders, wavelet scattering, and deep neural networks"	Techniques for extracting features from cropped photos are essential for gathering pertinent data. These methods turn raw pixel data into beneficial characteristics that machine learning algorithms can employ for detection and classification. Local Binary Patterns (LBP), Scale-Invariant Feature Transform (SIFT), and Histogram of Oriented Gradients (HOG) are frequently used feature extraction techniques [3].
Texture Analysis	Texture Analyzers	Texture patterns in cropped photos are analyzed and quantified using texture analysis. Information on disease signs and pest infestations can be gleaned from textural characteristics [4]. Methods including Grey Level Co-occurrence Matrix (GLCM), Gabor filters, and Local Binary Patterns (LBP) are frequently utilized for texture analysis in crop health detection.
Spectral Analysis	Multiple Electromagnetic spectrum	The use of methods like the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) in the spectral analysis allows for the monitoring of multiple electromagnetic spectrum bands, allowing for the detection of stress brought on by diseases or pests [21].
Hyperspectral Imaging	HyperCube	Hyperspectral imaging is an advanced method that takes pictures of several distinct and close-by spectral bands [29]. This permits thorough examination of crops, identifying minute variations in their spectral signature linked to ailments or pests.
Image Segmentation	Python Programming Languages	Image segmentation algorithms divide the cropped photos into discrete sections, distinguishing between portions of healthy plants and those that are infested with pests or diseases [34]. This stage is essential for isolating and locating specific crop problems. In crop health analysis, methods including thresholding, region-growing, and clustering are frequently employed for picture segmentation.
Machine Learning and Deep Learning	Python	Machine learning and deep learning algorithms are extensively utilized to detect diseases and pests in crops. These techniques enable automated pattern recognition, allowing the system to learn from labeled datasets and identify disease patterns in new images. Convolutional Neural Networks (CNNs) have shown exceptional performance in image-based disease detection tasks, with widely used models like ResNet, VGG, and Inception [5].

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Combining AI, machine learning, and computer vision approaches have significantly improved the identification of diseases and pests in crop lines utilizing image processing, image detection, image pixel analysis, and other techniques [2]. Combining these techniques enables creating precise and effective systems that will allow farmers to proactively manage crop health concerns, enhancing agricultural production and promoting sustainable farming practices.

Image processing and artificial intelligence (AI) are used to identify diseases and pests in crop lines [4]. These tools, approaches, and procedures substantially improve agricultural practices and increase food security. These methods and technologies' primary value comes from their early illness and pest infestation detection capabilities. Thanks to early identification, farmers can respond quickly and adopt tailored treatments to stop the spread of disease and reduce crop losses. Farmers can maintain crop health and ensure more excellent harvests by spotting problems before they spread. Precision agriculture is made possible by image processing and AI-based systems that let farmers apply treatments where required [6]. Farmers may maximize the use of pesticides, fertilizers, and water resources by locating the impacted regions, minimizing waste, and lessening the effect on the environment.

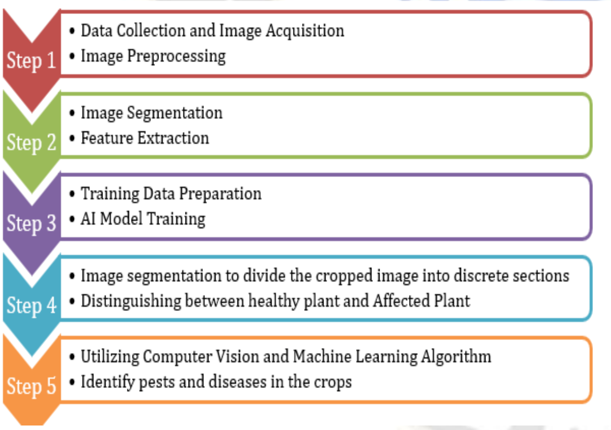

Fig 1. Image processing techniques

Additionally, this accuracy results in cost savings and more environmentally friendly agriculture methods. Processes for detecting diseases and pests are made more efficient by combining computer vision and machine learning technology. These automated algorithms are faster and more accurate than humans in analyzing large volumes of data. Due to its effectiveness, farmers can efficiently monitor enormous agricultural fields and make quick decisions based on real-time information.

Detecting pests and diseases in crops through image processing and AI techniques involves a series of mechanisms that leverage the power of computer vision and machine learning algorithms. A variety of methods that make use of the capabilities of computer vision and machine learning algorithms are used in the identification of pests and illnesses in crops using image processing, and AI approaches [1]. Gathering crop photos from multiple sources, including drones, satellites, and ground-based cameras, is the initial stage of the procedure. The visual depiction of the crops, including both healthy and damaged parts, is shown in these photographs. Preprocessing techniques are used after capturing pictures to improve their quality and eliminate noise or artifacts. Standard preprocessing techniques include image scaling, color correction, normalization, and filtering [7]. The crucial process of image segmentation divides the cropped picture into different parts to separate healthy plant portions from those afflicted by pests or diseases.

The segmented pictures are used to perform feature extraction, which extracts pertinent data. The cropped photos remove elements from healthy and damaged areas, including color histograms, texture descriptors, and form attributes [7]. A labeled collection of pictures with labels indicating whether they are healthy or infested with particular illnesses or pests is necessary to create an AI-based detection algorithm. The training data is produced by pairing the feature vectors derived from the pictures with the labels that go with them. A machine learning or deep learning algorithm is generally trained using the training data. Convolutional Neural Networks (CNNs), which excel in image analysis and feature extraction, are standard models [3]. The training teaches the model to identify patterns linked to agricultural diseases and pests. After training, a different dataset is used to validate and evaluate the model's effectiveness. The model's parameters can be fine-tuned to maximize its performance and improve its precision and generalizability. The model is prepared for disease and pest identification in new crop photos after it has been trained and verified. The trained model receives the preprocessed images and predicts whether each crop area is healthy or damaged [8]. The model's predictions are post-processed to compile the findings and produce a thorough output map highlighting the areas most affected by pests or illnesses. Farmers and agricultural specialists may use this data to make well-informed choices on targeted interventions like using suitable pesticides or putting specific disease management plans in place.

The detection procedure is a continual monitoring system rather than a one-time occurrence. The model can be retrained and refined as more data is gathered to react to shifting environmental factors and disease trends, ensuring the system is always current and efficient at spotting diseases and pests [7]. Therefore, data collection, image preprocessing,

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segmentation, feature extraction, AI model training, validation, and post-processing are all required to identify pests and diseases in crops using image processing and AI approaches [4]. By accurately and effectively identifying crop health concerns, this integrated method helps farmers make decisions quickly and control diseases and pests effectively, thus increasing agricultural output and sustainability.

III CRITICAL BACKGROUND ANALYSIS

In agriculture, pests, and illnesses offer severe problems and damages that harm the environment, the economy, and food production. Crop illnesses and insect infestations can destroy harvests, impacting farmers' livelihoods and global food security. The "Panama disease" or Fusarium wilt, brought on by the fungus Fusarium oxysporum, is one of the most well-known instances of severe disease in agriculture. This disease kills whole plantations of banana and plantain crops, resulting in considerable output losses. Once on a plantation, fusarium wilt spreads quickly via contaminated soil, making it challenging to grow bananas there for many years. The impact of this illness is significant because bananas are a primary staple food and export good for the agriculture sector.

Similarly, the "Citrus greening disease" or Huanglongbing (HLB) has become a significant worry for citrus producers all over the world [9]. Citrus trees are susceptible to this bacterial disease, which results in stunted growth, irregular fruit, and ultimately tree mortality. Major citrus-producing regions, including Florida in the United States, have suffered enormous losses due to HLB's extensive destruction of citrus crops. Due to the disease's quick spread, it is vital to conduct research, create disease-resistant strains, and devise efficient management methods [10].

The provision of food and means of sustenance to populations all over the world has placed agriculture at the forefront of human civilization. Insect infestations and crop diseases that threaten the food supply's safety are only a few of the challenges the business faces. The traditional methods and expert knowledge farmers relied on to recognize and address these issues were time-tested. These tactics' shortcomings, however, have severely impacted the environment and led to considerable losses in agriculture. The problems facing agriculture have been intriguingly solved by recent advancements in computer vision and artificial intelligence technologies [9]. It is now feasible to develop sophisticated tools and methods for maintaining and diagnosing crop health thanks to a significant growth in the usage of AI in agriculture. Examples include using data-driven analytics, machine learning algorithms, image processing techniques, and deep learning models [9]. With the development of AI-powered sensors, drones, and automated machinery, agricultural practices have been revolutionized by real-time monitoring, precision agriculture, and data-driven decision-making [10].

Crop diseases and pests are still severe problems for farmers worldwide. According to estimates from the Food and Agriculture Organization (FAO), crop pests and diseases globally reduce agricultural productivity by 20–40% annually [11]. Pest-related crop losses might exceed 50% in less developed countries. In addition to severely impacting food production, these losses have significant economic ramifications for farmers, leading to a decline in income and uncertain means of sustenance [12]. It is obvious that improved methods for spotting pests and illnesses are required, and AI presents an intriguing solution. Despite the potential benefits, some substantial barriers prevent AI from being widely used in agriculture. Lack of access to electricity, internet connectivity, and computer power might make it challenging to adopt AI-powered solutions.

Additionally, the cost of acquiring and maintaining AI systems may limit their availability to small-scale farmers. The quantity and quality of data present an enormous extra challenge. Accurate and comprehensive datasets are necessary for adequately training AI models. Nevertheless, getting labeled data for specific diseases and pests in agriculture might be complex due to resource constraints and identifying several crop health issues [9]. The need for standardized and well-annotated data makes it challenging to develop trustworthy and generalized AI models for different crops and regions.

Interdisciplinary cooperation between agricultural specialists, AI researchers, policymakers, and industry stakeholders is necessary for the adoption of AI in agriculture. To guarantee that AI solutions answer the unique demands and issues encountered by farmers and agricultural communities, bridging the gap between these areas and promoting knowledge sharing is crucial. These examples highlight the need to develop cutting-edge solutions to deal with crop diseases and pests in the context of the study subject on the application of AI for disease prevention and pest management in the agriculture business [13]. The effects of these diseases on crops like citrus and bananas lead to decreased production and financial hardship on farmers, reduced supply of necessary foods, and significant trade disruptions.

Infestations of pests pose severe problems for agriculture as well. For instance, the devastating pest, the "Fall Armyworm," may seriously harm crops, including rice, sorghum, and maize [14]. The Fall Armyworm, a native of the Americas, has quickly spread to other areas, devastating crops and jeopardizing global food security. The propensity of the bug to acquire resistance to traditional pesticides hampers

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control efforts further, prompting the investigation of creative pest control methods. To solve these problems and consequences, research on AI for disease prevention and pest control in agriculture has much potential. Farmers can quickly detect illnesses and insect infestations using AI tools and approaches [15].

Farmers can take prompt action to stop the spread of illnesses like Panama disease in bananas and Citrus greening in citrus trees via early identification and correct diagnosis. AI-driven pest monitoring can assist early insect detection, allowing farmers to deploy focused and efficient pest management techniques [14]. By maximizing the use of resources like pesticides, water, and fertilizers, AI-based systems may cut down on waste and adverse effects on the environment. Precision agriculture is made more reachable by combining AI with other technologies like drones and sensors, allowing farmers to monitor crops in great detail and make data-driven choices to protect them from pests and illnesses.

IV USE OF LITERATURE

A. Implementation Of Machine Learning TechniquesIn Agriculture

Using machine learning (ML) algorithms in precision agriculture has shown enormous potential in solving various issues and improving agricultural practices. Numerous agricultural applications have used different machine learning (ML) approaches, from production prediction to pest and disease detection in plants [15]. For a given agricultural application, choosing the best machine learning (ML) technique is essential to ensuring the accuracy and consistency of findings. Support Vector Regression (SVR) outperforms Artificial Neural Networks (ANN) in estimation accuracy due to its resilience in outliers and noise. In mapping soil organic stocks (SOC), ANN and SVRs have, nevertheless, demonstrated performance that is equivalent [2]. ANNs and SVRs have shown accuracy when predicting crop production, with the SVR model being computationally quicker.

On the other hand, methods like ANNs, Random Forests (RFs), and Support Vector Machines (SVMs) have produced excellent classifiers with high accuracy. Convolutional Neural Networks (CNNs), in particular, have demonstrated potential in segmenting agricultural picture collections using deep learning approaches [5]. Applying ML to precision agriculture still faces some unique difficulties. Therefore, it is crucial to have AI models that can adjust to missing data. Avoiding early disease and insect assaults may be impacted because current ML and DL models for plant disease and pest detection may not be appropriate for early detection. Therefore, early classification-focused deep learning models are essential for enabling prompt crop protection and intervention.

Table 2: Comparison of Machine Learning Techniques in the Agriculture

Technique	Complexity	Characteristics & Limitation	Current Application
ANN [30]	High	High power consumption; Susceptible to overfitting Require large datasets; Parameter tuning procedure is Time-consuming	Pattern laceration and attribute mapping: Crop estimation: Soil properties analysis and estimation
DTS [36]	Low	Sensitive to trial variations training data; Unstable occasionally: Susceptible to overfitting	Classifications Crop yield from sol variables to overfitting
SVM'S [37][29]	Low	Fast and accurate; Easy to implement Require small training samples; Robust to noise training data;|"Mostly seed for classification;	Classification of diseases Soil mapping: Retrieval of vegetation Attributes: Estimations
RFs [26]	High	Overfitting problem; High efficiency: High prediction performance: Small training Grime Easy parameterization	Attribute mappings classification and regression
DLs [32]	High	Highly promising for agriculture applications; High accuracy: Require large datasets; High computational cost	Classification and regression applications; Measure features: Yield estimation

The usage of CNNs in remote sensing applications for agriculture has continuously increased, but farmers' slow acceptance of UAV-based technology for specialized crops continues to be a barrier [5]. Widespread adoption is hampered by problems, including data preparation and analysis complexity and the need for current commercial solutions to deliver usable information.

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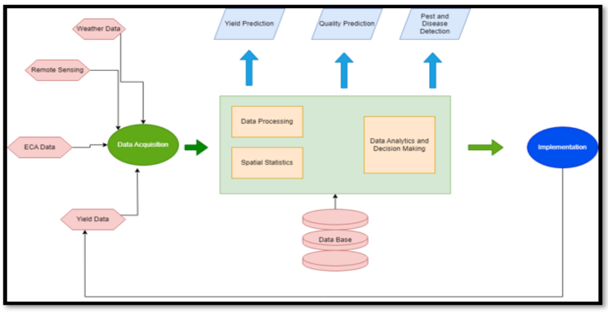

Fig 2. Precision Systems in Agriculture Using Big Data for image processing

Crop estimate, tree health detection, and disease monitoing may all be aided by employing UAVs in conjunction with big data analytics techniques like CNNs. IoT and sensor networks and ML-based significant data approaches like clustering and classification algorithms provide essential insights into soil properties [12]. Agriculture professionals can choose the best crops and cultivate them most effectively by studying information on the texture, structure, and chemistry of the soil. Large-scale agricultural data have been processed and analyzed using Spark Mlib and distributed parallel association rule mining techniques, enabling enhanced soil analysis and plant growth prediction [16]. In precision agriculture, ML algorithms have proven to help solve various problems and provide crucial information for making decisions. ML techniques, such as CNNs, SVMs, and deep learning, are essential to optimizing agricultural practices and assuring sustainable food supply, from crop yield prediction to disease detection and soil analysis [17].

B. Use Of CNN In Agriculture For Image Processing To Detect Disease And Crop Pests

Identifying plant diseases and pests in the agricultural sector has been transformed by applying deep learning techniques, notably Convolutional Neural Networks (CNN). CNNs are a subset of deep neural networks that are excellent at extracting complicated characteristics from big datasets and learning them automatically [16]. Detecting plant diseases and pests presents particular difficulties since it necessitates addressing the "what," "where," and "how" components of the issue. CNN accomplishes picture classification at the first step of detection, "what," by giving the image a label that specifies the type of illness or pest it contains. The second stage, "where," is where CNN precisely detects the disease or pest by pinpointing its exact location in the picture. Convolutional Neural Networks (CNN) image processing entails several crucial phases that allow the network to learn and extract pertinent information from the input pictures [18]. The intention is to utilize CNN to identify plant diseases and pests in the agricultural sector. The first stage is compiling a sizable dataset of labeled photos of healthy and diseased or pest-affected plants. The training data for the CNN is these photos. Thus, the images are preprocessed to maintain uniformity and eliminate any noise or extraneous information. To improve the training set's variety, preprocessing may comprise shrinking the photos, normalizing the pixel values, and enhancing the data.

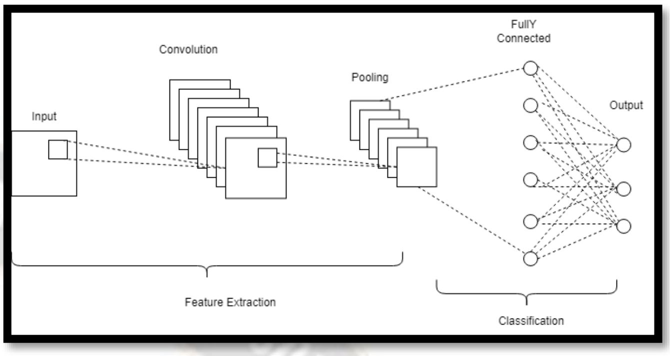

Fig 3. CNN Image processing steps in different layers

The core of CNN, the convolutional layers, as above figure, are in charge of feature extraction [16]. In this stage, the CNN performs convolution operations on the input picture by applying a series of learnable filters (kernels). Each filter picks up particular details in the image, such as edges, textures, or patterns. This layer produces a collection of feature maps, each showing the existence of a different feature in the input image. After the convolution procedure, an activation function adds non-linearity to the model [19]. ReLU (Rectified Linear Unit), a frequent activation function in CNN, aids the network in learning intricate correlations between features. Down-sampling feature maps and reducing the spatial dimensions of the data are done using pooling layers. Through this stage, overfitting is avoided, and computational complexity is reduced [20]. Max pooling is a popular method in which a small region of the feature map with the highest value is chosen to represent that region. Convolutional and pooling layer output is flattened before being fed into fully linked layers [18]. By connecting all neurons from the previous layer to all neurons in the current layer, these layers function as a conventional neural network. Making predictions using the collected characteristics and learning higher-level representations are both aided by this stage. The output layer of the CNN is the final layer and comprises neurons corresponding to the number of pest or disease classifications that need to be identified [16]. Each neuron in the output layer represents the likelihood that the input picture corresponds to a particular class. After training, a different collection of images that CNN has not seen during training are used to measure its performance [19]. How successfully the CNN recognizes illnesses and pests in hidden pictures is measured using criteria including accuracy, precision, recall, and F1 score.

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Convolutional layers are used for feature extraction during the CNN image processing process, pooling layers are used for down sampling, and fully connected layers are used for prediction [16]. After being trained on labeled data, the cnn is optimized to minimize the loss function. After training, the CNN may be applied to real-time detection and analysis in the agricultural sector, enabling prompt and precise diagnosis of plant diseases and pests. Identifying plant diseases and pests in agriculture has benefited dramatically from developing deep learning techniques, particularly CNN. CNN offers accurate and exact identification by addressing the unique problems of what, where, and "how," assisting farmers in making educated decisions and improving crop management techniques [20]. The usage of AI-based solutions is driven by the continued development of deep learning and its rising popularity, altering the agriculture sector and boosting its overall productivity and sustainability.

C. SVM Algorithm In Agriculture Related To Image Processing Techniques

The Support Vector Machine (SVM) algorithm has been followed in agriculture to detect diseases and crop pests with the image processing techniques performed by deep learning methods. The algorithm method has become an essential tool in agriculture, especially in image processing and AI for crop pest and disease prediction. With this accuracy, SVM's supervised machine learning method for classification and regression problems is ideally suited for spotting and identifying crop health issues from picture data. SVM is essential in agriculture for correctly recognizing and categorizing diseases and pests in crop images [21]. The SVM algorithm gains the ability to distinguish between distinct classes of crop health situations by training on labeled datasets that include both healthy and sick plant photos. However, it accomplishes this by constructing a hyperplane that maximizes the margin between the various classes to effectively separate and classify crop health statuses.

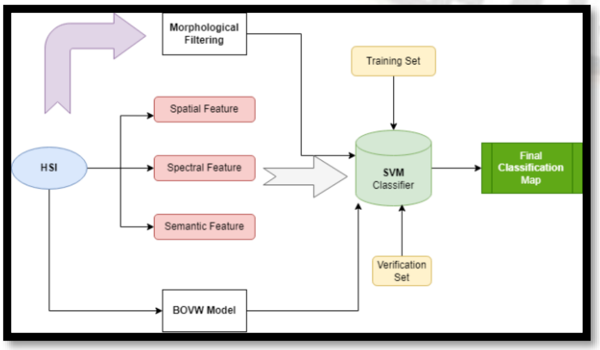

Fig 4. Illustration of the proposed SVM classification method for hyperspectral images

This algorithm helps locate contaminated areas within crop photos when image processing and AI are used to anticipate agricultural pests and illnesses. By examining visual features and patterns, SVM can accurately detect the presence and severity of diseases and pest infestations. This skill is essential for quick diagnosis and intervention, which enables farmers to take targeted action and reduce crop losses. The uses in agriculture of SVM improve resource management and precise farming techniques [18]. Farmers can use fewer pesticides and fertilizers while maximizing their efficiency by being able to apply treatments selectively depending on the recognized crop health conditions. SVM is a vital tool for real-time disease monitoring and decision-making in the agricultural industry because of its capacity to analyze massive amounts of visual data fast and reliably.

The utilization of robotics technology has the potential to automate various agricultural tasks, resulting in enhanced production and reduced labor requirements. Big data is prevalent in analyzing extensive agrarian datasets to get valuable insights and facilitate evidence-based decision-making. Machine learning algorithms enhance agricultural operations and predict outcomes by applying artificial intelligence (AI). The agri-food supply chain may be made more secure and transparent, which improves food safety and traceability. Monoculture and intensive animal husbandry are standard practices today. However, they present environmental, human health, and animal welfare problems. Agriculture is lagging in terms of intelligence and technology.

Additionally, there needs to be more intelligence in managing the agri-food supply chain. These difficulties can be overcome by incorporating Industry 4.0 technology into agriculture, opening the door for more efficient and sustainable industrial agriculture.

Consequently, Agriculture 4.0 is a transformational concept that aims to use cutting-edge technology to overhaul the agriculture sector completely. Industrial agriculture may increase production, improve resource management, and enhance food safety by implementing IoT, robots, big data, AI, and blockchain. Thus, there are still obstacles to overcome to fully realize the potential of Agriculture 4.0 and build a sustainable future for the agricultural industry.

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Table 3: Types of Techniques in the Agriculture

Image Datasets	Devices	Category	Before Annot-ations	Techni-ques	After Annotat-ions
Potato [13]	Graphics Processing Unit	RGB	4062	CNN	Not Mentioned
Potato [17]	Fine-Tuned CNN	RGB	2108	SVM	Not Mentioned
Apple [22]	Deep Convolutional Neural Network	RGB	3642	SVM	547
Raspberries [23]	computer vision processing	RGB	286	CNN	8
Corn [23]	Mobile	RGB	3852	CNN	513
Tomato [24]	Not Mentioned	RGB	17,859	SNM, KNN	Not Mentioned
Rice [25]	Not Mentioned	RGB	1600	CNN	400
Cucumber [26]	Not Mentioned	RGB	600	Entropy-ELM Feature Selection	2000

The table gives a general overview of several image datasets, their categories, devices used for image acquisition, cropping strategies, and image models utilized for processing. It includes a variety of produce, including cucumber, potato, tomato, apple, strawberries, corn, and tomatoes. The images used in each dataset have various levels of categorization and annotation. However, there are aspects of some listings that need to include explicit information about cropping methods. The number of photos before and after annotation highlights the efforts to enrich the datasets. All datasets have RGB as the color representation. The tool used to take the photographs varies across datasets. It may include references to "Mobile Devices" and "Graphics Processing Units (GPU)" in some situations, while other entries may be ambiguous about the tool utilized.

Regarding the picture models, the table indicates that the datasets were processed using "Deep Convolutional Neural Network," "Fine-Tuned CNN," and "Standard CNN." For the Tomato dataset, "support vector machines (SVM)" and "k-nearest neighbors (KNN)" applications are acknowledged, demonstrating the use of machine learning algorithms outside of the image as mentioned in earlier models [17] [22]. There should be analyzed that some items in the table need more complete information, making it difficult to thoroughly evaluate all features of the datasets, even though the table provides insightful information about each dataset's properties. Despite this, the collection offers various picture datasets that embrace many categories and methodologies, serving as a valuable reference for scholars and practitioners interested in image processing and computer vision.

Table 4. Different crops and algorithms with accuracy

Article No.	Crop	Pest and Disease Names	No. of Images	Processing Methods	Algorithm used	Accuracy
27	Corn	Gray Leaf Spot (GLS), Northern Leaf Blight (NLB), and Northern Leaf Spot (NLS)	200	Semantic segmentation using the custom dataset	SegNet	0.9422%
28	Potato	Late Blight	Not Mentioned	Computer Vision	CNN	96%
29	Wheat	Wheat Rust	300	Spectral analysis	Support Vector Machines	85%
30	Rice	Rice Blast	800	Drone-based imagery	Deep Learning	88%
31	Soybeans	Soybean Cyst Nematode	400	Hyperspectral imaging	Random Forest	90%
32	Cotton	Cotton Bollworm	600	Remote sensing and satellite	Artificial Neural Networks	87%
33	Tomato	Early Blight	Not Mentioned	Not Mentioned	YOLOv3 model	98.3%

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Agriculture disease management has been transformed by AI, notably in terms of identifying and controlling agricultural pests and diseases. In the maize research [27], SegNet identified illnesses, including Grey Leaf Spot and Northern Leaf Blight, with an accuracy of 94.22%, allowing for more focused treatment efforts and less pesticide use. A CNN model detected Late Blight in potatoes [28] with 96% accuracy, enabling early disease detection and management. With spectral analysis and SVM, the Wheat Rust in [17] on wheat was identified with 85% accuracy, allowing for early disease detection. Deep learning algorithms and drone-based photography in rice [30] enabled 88% accuracy in detecting Rice blasts, enabling efficient disease surveillance. With hyperspectral photography and Random Forest decreased soybean production losses with 90% accuracy in identifying soyabean cyst nematodes [31]. To improve pest management, ANN and remote sensing data for cotton [32] detected Cotton Bollworms with 87% accuracy. Last, tomatoes [33] showed 98.3% accuracy in the YOLOv3 model in Early Blight diagnosis, avoiding disease spread and lowering losses. These developments demonstrate how AI transforms agriculture, fosters effective crop production, and reduces dependency on hazardous pesticides.AI offers hope for a resilient and fruitful future in international agriculture [37].

V PERFORMANCE INDICATORS OF TOOLS AND TECHNIQUES

Evaluating the efficacy and efficiency of instruments and procedures used in diverse sectors, including agriculture, requires using performance indicators or metrics. These metrics assess how effectively a model or algorithm performs in detecting disease, forecasting agricultural yields, and identifying pests.

A. Accuracy

The accuracy of a model's predictions is a measure of its general correctness. It is the proportion of occurrences that were successfully predicted for all of the examples in the dataset.

Equation:

$$\text{Accuracy} = (TP + TN)/(TP + TN + FP + FN)$$

Variables:

"TP (True Positive): The number of positive instances correctly classified as positive."

"TN (True Negative): The number of negative instances correctly classified as negative."

"FP (False Positive): The number of negative instances incorrectly classified as positive."

"FN (False Negative): The number of positive instances incorrectly classified as negative."

B. Positive Predictive Value (PPV)

The precision of a model's accurate predictions is measured. The ratio of accurate optimistic forecasts to all optimistic predictions determines this.

$$\text{PPV} = (TP)/(TP + FP)$$

C. True Positive Rate (TPR)

The recall measures the accuracy with which a model can recognize positive cases. It is the proportion of accurate optimistic predictions to all positive examples in the dataset.

Equation

$$\text{TPR} = (TP)/(TP + FN)$$

D.True Negative Rate (TNR)

A model's specificity score indicates how well it can recognize negative examples. It is the proportion of accurate pessimistic predictions to all the negative examples in the dataset.

$$\text{TNR} = (TN)/(TN + FP)$$

E. F1-Score (F1)

The harmonic mean of recall and accuracy is known as the F1-Score. It strikes a compromise between the trade-off between memory and accuracy and offers a single score that represents the overall effectiveness of the model.

$$\text{F1} = 2*\text{PPV}*\text{TPR} / (\text{PPV} + \text{TPR})$$

F. Mean Absolute Error (MAE)

The average absolute difference between the actual and anticipated values is measured by mean fundamental error or MAE. In regression problems, it is often employed.

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n} |yi - \hat{y}_i |$$

"Y_i = Actual value of the i-th instance."

"$\underline{Y_i}$ = Predicted value of the i-th instance"

"n: Total number of instances"

These performance indicators are essential for directing models' creation, improvement, and evaluation. They assist agricultural researchers and practitioners in determining which models are most appropriate for specific tasks, identifying potential areas for improvement, and validating the effectiveness of their tools and procedures. They offer precise, unbiased measurements of how effectively a model or algorithm completes its designed task. Stakeholders may improve agricultural practices, increase crop management, maximize

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resource use, and guarantee food security by using these measures to guide their decisions.

VI ADVANTAGES OF AI TOOLS AND TECHNIQUES IN THE AGRICULTURE

Numerous benefits come with using AI in agriculture to avoid illness, which is crucial to successfully controlling crop pests.

Table 5. Advantages of AI

Advantages	**Descriptions**
Early Detection	AI-powered systems can instantly analyze enormous volumes of data from several sources, such as pictures, sensor data, and meteorological information [35]. This makes identifying agricultural diseases and pests possible before they spread widely. Early identification allows farmers to respond quickly and put targeted measures in place, stopping the spread of illnesses and reducing crop losses.
Accurate Diagnosis	Based on patterns and characteristics collected from photos or data, AI systems can precisely detect and diagnose certain crop diseases and pests [36]. By ensuring that the proper steps are taken to counteract the dangers that have been seen, this precision lowers the possibility of incorrect diagnoses and pointless treatments.
Accurate Diagnosis	Based on patterns and characteristics collected from photos or data, AI systems can precisely detect and diagnose certain crop diseases and pests [36]. By ensuring that the proper steps are taken to counteract the dangers that have been seen, this precision lowers the possibility of incorrect diagnoses and pointless treatments.
Precision Treatment	Thanks to AI-driven precision agricultural approaches, farmers may only use treatments and interventions where necessary [32]. This lessens the need for pesticides and other chemicals, reducing their adverse environmental effects and increasing sustainability.
Timely Interventions	AI systems can give farmers immediate alerts and recommendations thanks to real-time monitoring and predictive capabilities [30]. Farmers can act rapidly in the face of changing circumstances and take precautions to safeguard crops from potential disease outbreaks.
Enhanced Resource Management	By optimizing resource usage, such as water, fertilizers, and pesticides, AI helps reduce wastage and cut down production costs [9]. This leads to increased efficiency in agricultural practices and improved profitability for farmers.

VII CHALLENGES AND WEAKNESS OF AI TOOLS AND TECHNIQUES

Although AI has much to offer regarding disease prevention and pest control in the agricultural sector, it also has some issues and flaws that must be fixed for its deployment to be effective. AI systems primarily rely on vast and high-quality datasets for training and precise prediction. However, it might not be easy to find complete and varied datasets in agriculture. Inadequate, biased, or incomplete data may impact the effectiveness and generalizability of AI models. Inconsistencies in the datasets used to train AI models may result from a lack of data collection, annotation, and labeling standardization. This may lead to variances in model performance and make it challenging to compare the outcomes of various investigations.

Many agricultural areas need more basic infrastructure and internet access, particularly in remote areas. As a result, AI solutions that rely on real-time data processing are more difficult to implement and operate. Deep learning models, in particular, are sometimes called "black boxes" because of how opaque their decision-making is. Gaining the trust of farmers and other stakeholders can be tricky since it might take time to interpret the reasoning behind model forecasts. Large-scale AI implementation can be expensive and resource-intensive.

The use of AI technology by small-scale farmers may need to be improved financially, restricting their access to the advantages of cutting-edge disease prevention and pest control strategies. When AI models outperform expectations on training data but fall short on real-world scenarios, this is known as overfitting. AI's efficacy in various agricultural situations depends on balancing model complexity and generalization. AI deployment may have unforeseen environmental effects even if it can reduce chemical use and improve resource allocation. We must carefully assess the long-term impacts of agricultural practices powered by AI on biodiversity and ecosystems. Data privacy, ownership, and access concerns are brought up by the use of AI in agriculture.

Farmers must be able to manage their data and have confidence that AI technologies are being utilized morally and sensibly. Farmers' dependence on conventional wisdom and expertise may decline due to extensively relying on AI for disease prevention and pest control. Striking a balance between technical improvements and traditional farming practices is crucial. Farmers need to be educated and trained if AI technologies are to be adopted widely in agriculture. To fully utilize these technologies, one has to be proficient with AI tools, data interpretation, and utilization techniques.

VIII CONCLUSION

In conclusion, applying AI technology to agriculture has the potential to completely transform pest control and disease prevention, resulting in enormous breakthroughs in the sector. Farmers can identify and control crop diseases and pests more effectively than ever by utilizing AI's sophisticated algorithms and machine learning skills. Early illness identification and prompt treatment are made possible by AI's capacity to analyze massive datasets from multiple sources, including photos, sensors, and meteorological data. With the help of this early warning system, farmers can act quickly to stop the spread of illnesses and reduce crop losses. Furthermore, AI-driven precision agriculture enables focused interventions and optimized resource use, minimizing the adverse effects on the environment and raising sustainability overall. AI's precise diagnosis and assistance for data-driven decision-making make it essential for disease prevention in agriculture. AI enables farmers to manage crops more effectively by offering trustworthy and unbiased information, increasing agricultural yields and food security. AI solutions are practical for both small-scale and large-scale commercial farms because of their scalability and accessibility, which benefits farmers in various agrarian contexts.

Therefore, there are some issues and areas for improvement in applying AI to agriculture. Several obstacles must be overcome, including connection, infrastructural limitations, lack of standardization, and data availability and quality. Successful AI deployment also requires considering factors like controlling unanticipated environmental repercussions, preventing overfitting, and ensuring model interpretability. Despite the tremendous prospects that AI offers the agricultural sector, its ethical ramifications, farmer education, and legal and regulatory concerns need to be carefully considered. Achieving sustainable and ethical agrarian growth requires integrating AI technology while maintaining a healthy respect for conventional wisdom and methods.

Collaboration between academics, decision-makers, and stakeholders is crucial to realizing AI's potential in agriculture fully. We can build an agriculture ecosystem that uses data-driven insights and technological innovations to overcome challenges caused by diseases and pests and improve productivity, efficiency, and food security for a more sustainable future by addressing the challenges and weaknesses and encouraging responsible AI implementation.

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