LITERATURE REVIEW

AI-powered plant disease detection approaches use machine learning and computer vision techniques to reliably identify and diagnose illnesses, allowing for timely intervention and successful management measures.
Symptom-based diagnosis guides aid in identifying plant diseases based on symptom-like characteristics. However, they have limitations in accuracy and specificity due to overlapping symptoms and multiple causal agents. Traditional methods, while crucial for agricultural pest management, may become outdated or inaccessible in remote regions. (2)

The integration of AI technologies, such as machine learning and computer vision, has the potential to overcome existing restrictions, allowing for the automated, precise, and fast diagnosis of plant diseases.

Early disease detection enables farmers to identify and manage disease outbreaks before they cause irreversible damage. **Precision agriculture** optimizes input distribution using AI-driven technology based on real-time crop health and disease prevalence evaluations. **Disease monitoring and surveillance** allow for continuous crop health monitoring and the early detection of disease outbreaks over huge agricultural areas.
Decision Support Systems (DSS) offer individualized suggestions and actionable insights to improve crop management methods and reduce disease risks. These systems use machine learning algorithms to assess various information, allowing farmers to make more informed decisions, optimize resource allocation, and maximize yields while reducing input costs and environmental effects. (1)

Viticulture, the historic art of cultivating grapes, is facing new problems as a result of worldwide market demand and environmental concerns.

Precision agriculture strives to improve farming accuracy, efficiency, and sustainability by leveraging new technology. (3) The system is designed for vineyard disease identification and treatment. Users upload an image of a vine leaf, which is processed and presented with a classification label and confidence score. The system's user-friendly interface allows quick comparison with annotated images, benefiting technicians. Once classified, the system uses geo-tagging to link disease instances with specific locations and timestamps.

This map-based interface helps winegrowers identify disease hotspots, apply targeted treatments, and optimize vineyard management.

Integrating disease classification with weather and satellite data visualization offers a holistic approach to precision viticulture. (3)

Rice is a staple food consumed by over 50% of the world's population, making it a critical component of global food security. Rice crops are susceptible to several diseases caused by bacteria, viruses, fungus, and other pathogens. Diseases can harm crops and lead to food shortages, causing major hardship for affected people.
The study found that a proposed approach to classifying rice diseases using **SVM** and **HOG** features achieved an accuracy of 95.63%, comparable to state-of-the-art techniques. The **edge detection** method was more effective in distinguishing between leaf-affecting diseases and subtle differences in plant appearance. The combination of edge detection and HOG features outperformed using edge detection or HOG features alone.(4)

Common beans (CB) are essential for nutrition and economic stability in Africa and Latin America. However, cultivation poses a threat to diseases, reducing yield and quality. Detecting diseases using visual symptoms is challenging due to variability. An AI-driven system uses deep learning and object detection technologies for rapid and cost-effective detection. (5) The study analyzed a large picture dataset utilizing data augmentation techniques and annotation on three sophisticated **YOLO designs (YOLOv7, YOLOv8, and YOLO-NAS)**. The model was trained using the **'LabelImg'** program, and micro-annotations were employed to improve its effectiveness in detecting common bean illnesses. The models were evaluated using real-world photos from disease hotspots in Latin America and Africa.The YOLO-NAS model detected virtually all classes with near-perfect accuracy and high confidence ratings, with the exception of pod classes. (5)

Early blight, a widespread potato disease in North America, affects less productive and older leaves, causing senescence. Currently, management entails consistent fungicide spraying, which raises production costs and has an environmental effect. An intelligent categorization system can increase economic and environmental sustainability by recognizing unhealthy plants and applying fungicides in a targeted manner. (6) The study discovered that **EfficientNet** and **VGGNet** beat GoogleNet in illness detection, with **EfficientNet performing best in 4-class and 6-class CNNs**. CNNs can reliably detect early blight disease in potato plants, with validation accuracy ranging from 0.92 to 1.00. EfficientNet outperformed in both individual and combined stages, making it ideal for real-time applications. The study's goal is to create a smart sprayer capable of accurately detecting diseases.

A novel method for effectively identifying tea leaf illnesses utilizing artificial intelligence techniques that preprocesses input photos, extracts features with a hybrid pooling-based convolutional neural network (CNN), and detects disease using a weighted random forest (WRF) model. Each tree's weights are assigned using the Cuckoo Search Optimization (CSO) approach.The Tea Sickness Dataset (TSD) is used to determine the method's efficacy. The approach has an average accuracy of 92.47% in detecting seven different types of tea leaf diseases, with recall and accuracy metrics of 92.35 and 92.26, respectively.
The proposed technique for illness diagnosis may have drawbacks in terms of disease detectability and diagnostic accuracy.
CNN models require a big training dataset, which can lead to overfitting difficulties. Furthermore, the strategy increases model training time by at least 3.11%, which affects the method's overall efficacy.

Horticulture, a rapidly growing sector in India, faces challenges such as land utilization, labor shortages, water shortages, low soil fertility, early disease detection, pest control, crop monitoring, and yield prediction. A case study of plant leaf disease detection and classification using Convolutional Neural Network (CNN) was presented, achieving training and validation accuracies of 0.69 and 0.86, respectively, with training and validation losses of 1.05 and 0.53 respectively.(8)

GranoScan is a smartphone application that detects and identifies over 80 risks to wheat in the Mediterranean area. It has a graphical interface suited for in-field illumination conditions, a user-friendly interface, operability in low or no connection, a simple operational guide, and the option to designate an area of interest for focused threat detection. The program employs a deep learning architecture known as efficient minimum adaptive ensembling to create accurate artificial intelligence models. GranoScan performs well in in-field pictures, with mean accuracy rates of 77% to 95% for leaf diseases, spike, stem, and root diseases, and up to 94% for pests.
The app uses an ensemble strategy with two instances of the EfficientNet-b0 architecture and has a large dataset of almost 70,000 images for robust training and validation. (9)

Groundnut, a crucial crop, is experiencing a productivity drop owing to leaf diseases. LeafNet, a new architecture for identifying six key classes of groundnut leaf diseases using a dataset of 10,361 pictures. The architecture's performance is assessed using both subjective and objective assessment methods. LeafNet's strong performance is due to residual networks and weight initialization strategies. It outperformed other neural network designs with test accuracy of 97.225%, precision of 97.365%, recall of 97.225%, F1-score of 97.225%, and MCC of 96.700%. The architecture's flexibility and generalizability are evaluated using a variety of leaf disease datasets.(10)

The Crop Disease Prediction in Smart Agriculture research focuses on the application of machine learning and deep learning techniques for detecting and predicting crop diseases, particularly in cotton crops. The significant impact of crop diseases on agricultural yield and economic losses underscores the need for more accurate and timely disease diagnosis. Traditional methods, relying on manual inspection, are time-consuming and prone to error, making the use of deep learning, especially convolutional neural networks (CNNs), an attractive alternative. By leveraging a well-curated dataset of cotton leaves a ected by various diseases, the researchers achieve high accuracy in disease detection, with the future potential to explore federated learning models and multi-scale feature extraction techniques. Building on this foundation, the DeepCrop Research takes a similar approach but expands the scope by focusing on multiple crops and leveraging the PlantVillage dataset, containing over 10,000 images. This research emphasizes the critical need for early plant disease detection to avoid economic losses for farmers and to improve agricultural productivity. One of the key challenges addressed is the overfitting and ine ciency of traditional machine learning models, which struggle with smaller datasets. Here, advanced CNN architectures like ResNet-50, VGG-16, and VGG-19 yield impressive accuracy rates, with the best performing model achieving 98.98% accuracy. The development of a smart web application allows real-time disease diagnosis by farmers, providing immediate and actionable insights. The convergence of findings from both studies emphasizes the growing importance of deep learning models in real-world applications, as well as the need for further exploration into integrating diverse datasets and enhancing models' performance across di erent crop types. In a similar way, the AI and Deep Learning in Crop Disease Management Research highlights the potential of artificial intelligence (AI) and deep learning in identifying emerging diseases and predicting pests, with a focus on common beans (Phaseolus vulgaris L.). Traditional plant disease management is labor-intensive, expensive, and often environmentally damaging. By utilizing deep learning models capable of automated feature extraction, the researchers o er cost-e ective and scalable solutions. Though the research does not detail specific datasets, it highlights the necessity for diverse and large datasets for training robust models. The potential for integration with Mobile Edge Computing (MEC) systems could significantly enhance the real-world applicability of these solutions, especially in resource-constrained agricultural settings. The increasing role of deep learning models discussed in this paper resonates with the findings of the DeepCrop Research, reinforcing the importance of leveraging large-scale datasets like PlantVillage to improve prediction accuracy and reduce costs. The Research on Machine Learning for Crop Diseases and Pests Prediction presents a comprehensive survey on machine learning techniques applied to agricultural disease and pest management. The research emphasizes the growing global population and the need for increased crop productivity, which pests and diseases undermine. Challenges such as intraclass variability and environmental conditions during image acquisition complicate performance comparisons among studies. Similar to the AI and Deep Learning study, this research stresses the importance of diverse data modalities to improve forecasting accuracy, aligning with previous findings on the role of datasets. By addressing the challenges of dataset variability and focusing on systematic reviews of machine learning (ML) techniques, this research suggests the necessity for deep learning approaches in improving disease and pest management strategies. It draws a parallel to the earlier studies' emphasis on CNNs and real-time applications in agricultural settings. Expanding on this theme, the Research on Machine Learning Models for Plant Disease Prediction and Detection explores various machine learning models for identifying plant diseases and highlights the limitations of traditional identification methods. Here, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and ensemble methods are compared, with datasets like Kaggle and PlantVillage playing a pivotal role in training models. Much like the earlier studies, the importance of accurate, high-performance models for real-time agricultural use is emphasized, with future research pointing towards deep learning and transfer learning as promising directions. The focus on improving computational e ciency complements earlier discussions on the importance of model performance in practical applications. The role of AI is further explored in Plant Disease Detection using AI, which emphasizes the importance of artificial intelligence in detecting plant diseases across various crops in India. This study aligns with previous research by addressing the limitations of manual disease detection methods and highlights the growing reliance on machine learning and deep learning models. By utilizing image acquisition, segmentation, feature extraction, and classification, the research proposes comprehensive AI-driven solutions for real-time plant disease detection. As seen in other studies, the use of large datasets for training models remains a recurring theme, with the need for more comprehensive datasets to enhance performance being a key takeaway. Similarly, the Role of Artificial Intelligence in Agriculture research delves into AI's capacity to address agricultural challenges, including plant diseases. The study highlights advanced AI techniques such as Few Shot Learning (FSL) and Generative Adversarial Networks (GANs), which aim to improve plant disease detection, even with limited data. Much like the other research on AI-driven models, this study emphasizes the importance of data availability and augmentation, linking back to the DeepCrop and AI in Crop Disease Management studies. The need for multimodal data fusion and integration of IoT platforms for real-time disease detection and monitoring is another thread connecting this research with others. In contrast to the centralized model training discussed in previous research, the Image based Crop Disease Detection with Federated Learning introduces a novel approach to preserving data privacy while still enabling e ective model training. Using CNN models, including ResNet50, and attention-based models like vision transformers (ViT), the study highlights federated learning's potential to enhance disease detection without compromising on data privacy. This study ties into previous research by utilizing the PlantVillage dataset and reiterating the importance of high-quality data and the need for hyperparameter tuning for larger and more complex datasets. The exploration of federated learning as a future research direction complements earlier discussions on the necessity of scalable, real-world solutions for farmers. Lastly, the AI-Driven Solutions for Precision Crop Disease Management and Plant Disease Detection Using CNN focus on the development of CNN-based systems for automated plant disease detection. These studies echo earlier findings about the ine ciencies of manual detection methods and highlight CNN architectures, such as Xception and DenseNet121, f ine-tuned for plant disease classification. These systems provide real-time diagnosis through web and mobile platforms, thereby streamlining disease management for farmers. By incorporating IoT devices and real-time monitoring, these studies align with the earlier discussion on AI and IoT integration for enhanced agricultural practices.

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1.Crop disease detection using image segmentation using K-Means clustering technique.

The proposed method focuses on detecting and recognizing leaf diseases using image processing and an improved K-Means clustering algorithm. RGB images of leaves are first acquired, and a color transformation structure is created to convert the images from RGB to another color space. K-Means clustering is then applied to segment the images, where mostly green pixels, representing healthy areas, are masked using Otsu's method. These masked and boundary pixels are removed to enhance disease identification accuracy and reduce processing time. The infected regions are converted from RGB to HSI color space, and Spatial Gray-Level Dependence Matrices (SGDM) are generated for the Hue and Saturation channels. Texture statistics are computed for the infected areas using the Gray Level Co-occurrence Matrix (GLCM) method. These features are then used in a recognition process, where a pre-trained neural network classifies the images. The system's performance is compared against different classifiers, such as Mahalanobis minimum distance, neural networks using backpropagation, and radial basis functions, to identify the most effective method. This improved approach enhances clustering accuracy by filtering out noise and achieves better recognition of leaf diseases.The notable technologies used are K-Means clustering Algorithm,Ostu method,SGDM Matrix Generation (Stochastic Gradient Descent with Momentum). We present a k-means-based clustering algorithm that efficiently identifies natural clusters in datasets, whether in original space or subspaces. Like traditional k-means, it has linear time complexity. Experimental results demonstrate high clustering accuracy, making it an effective method for data mining analysis.

2.Applicability of broadband high spatial-resolution ADAR (Airborne Data Acquisition and Registration) remote sensing data to detect rice sheath blight and developed an approach to further explore it.

Field sampling was conducted in a rice field during August and September 1999 to estimate the severity of infection. The field was divided into 11 strips, and samples were collected at approximately 50 sites per strip by walking centrally along each strip. Infection severity at each site was assessed based on three measurements: the percentage of infected tillers (sheath blight), the height of sheath blight symptoms above ground, and the height of the plant canopy. These measurements were used to construct a field disease index (DI) for each site.In parallel, airborne remote sensing images were acquired on four different dates using the ADAR system, which captured four spectral bands (blue, green, red, and near-infrared). The images were processed using ENVI 3.4 software to extract data corresponding to field sampling locations. Ratio and standard difference indices were computed from the image data to detect the presence of sheath blight. Linear interpolation was employed to match field sampling dates with imaging dates.A method was developed to estimate infection severity from the remote sensing indices, using indices such as RI14, SDI14, and SDI24. This method was validated through statistical analysis, demonstrating its effectiveness in identifying infected plants.The maim technologies are ENVI 3.4,RSI,NDVI,SVM. Only band 4 (near-infrared) had a relatively higher correlation ($R = 0.5928$), explaining just one-third of the disease variations. Lower infection severity ($DI < 10$) pixels exhibited little change, while higher severity points ($DI > 10$) showed some correlation. This suggests that the disease was difficult to directly identify from wide-band images, indicating the need for more precise methods for accurate detection.

3. Exploration of machine learning approaches for automated crop disease detection

Wheat, rice, and maize represent 80% of cereal production and are staple foods worldwide. Wheat faces significant diseases, including rust and Fusarium head blight, leading to severe yield losses. Rice is affected by bacterial blight, leaf blast, and brown spot, while maize suffers from leaf blight and rust.Early disease detection is crucial but often overlooked in traditional visual inspections. Artificial intelligence, especially machine learning (ML) and deep learning (DL), provides advanced solutions for timely identification of crop diseases. This review evaluates various ML/DL models in crop disease detection, assessing their effectiveness and applications to enhance agricultural sustainability. Unlike traditional programming, these systems identify patterns and make decisions based on input data. Various types of machine learning techniques support efficient model training:Supervised Learning uses labeled input-output pairs.Unsupervised Learning finds patterns without labeled data.Reinforcement Learning involves agents learning through interaction with an environment, receiving feedback via rewards or penalties.Semi-supervised Learning combines labeled and unlabeled data, particularly useful when labeled data is scarce.Transfer Learning applies knowledge from one task to enhance performance on a related task.Ensemble Learning merges multiple models to improve accuracy. In this analysis, we reviewed 2008 documents to identify 30 articles focused on machine learning (ML) and deep learning (DL) models for detecting crop diseases in staple crops like rice, wheat, and maize. We evaluated methodologies, accuracy rates, feature extraction methods, and dataset sources, highlighting models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Support Vector Machines (SVMs), and advanced architectures like ResNet.

4. Development of convolutional neural network models to perform plant disease detection test.

Development of convolutional neural network models to perform plant disease detection test.Identifying spot infections on leaves, categorizing them with machine learning algorithms such as Learning Vector Quantization (LVQ), Feed Forward Neural Networks (FFNN), and Radial Basis Function Networks (RBFN). Their system effectively diagnosed diseased leaves using shape and texture data, supporting a machine learning-based approach to improve crop quality in India and detecting cotton leaf diseases through image capturing and feature extraction using HSV color data, training an Artificial Neural Network (ANN) to distinguish between healthy and diseased samples.Also explored real-time recognition of tomato diseases using three deep learning detectors. A deep CNN based on AlexNet for apple leaf diseases achieved 97.62% accuracy. Development of a neural network model for image classification, to be deployed in an Android application for live detection of plant leaf diseases via smartphone cameras. This involves data collection from the PlantVillage Dataset, preprocessing with Image-data generator API, and building a CNN model based on VGG-19 architecture.

5. Recent Advances in Crop Disease Detection Using UAV and Deep Learning Techniques

Remote sensing is vital for precision agriculture (PA), enabling non-destructive monitoring through data from reflected energy. It includes three main techniques:

Field-Based Sensors,Satellite/Aircraft,Based Sensors.Provide high spatial resolution and flexibility, allowing for frequent field revisits. UAVs can be fixed-wing for large areas or rotary-wing for vertical takeoff and landing.UAVs capture light spectra from crops, facilitating the use of vegetation indices (VIs) like RGB, multispectral, and hyperspectral VIs. Machine learning (ML), particularly deep learning with convolutional neural networks (CNNs), enhances agricultural data analysis for tasks like yield prediction and disease detection. This section discusses UAV platforms, their configurations, and their impact on crop disease estimation methods. It also reviews successful VIs in disease detection and analyzes advanced ML and deep learning methods, concluding with limitations, challenges, and future directions for UAV-based crop disease estimation.

6. AI-driven system for rapid and cost-efective CB disease detection, leveraging state-of-the-art deep learning withYOLO driven deeplearning to enhance agricultural AI

We used *LabelImg* software to annotate disease-infected areas in our dataset by drawing bounding boxes around affected regions and assigning class labels. Annotations were saved as XML files and converted to YOLO format for compatibility. Precision was key, with annotations focused on enclosing common bean leaves and pods in the smallest rectangles to reduce background noise. This resulted in about 9969 whole-image annotations. Additionally, micro-annotations were performed on individual spots or lesions, improving disease detection accuracy, leading to 34,053 detailed annotations. Data augmentation techniques were applied to balance the dataset. Micro-annotations and data augmentation techniques enriched the dataset, improving CNN model performance for disease identification in real-world conditions.

7 Plant disease detection based on data fusion of hyper-spectral and multi-spectral fluorescence imaging using Kohonen maps

The **Multi-Spectral Fluorescence Imaging System (MFIS)** is designed to capture fluorescence emitted by plants to detect health and stress levels. It works by using a 10-bit CCD camera linked to an optical beam splitter, which divides the field of view into four identical sub-images. Each sub-image is filtered at specific wavelengths (450 nm, 550 nm, 690 nm, and 740 nm), allowing detailed analysis of fluorescence at these bands. To detect the plant-specific areas, the **Normalized Difference Vegetation Index (NDVI)** is used. NDVI helps identify leaves by measuring the difference between near-infrared (740–760 nm) and red (640–620 nm) light reflection, which distinguishes plant matter from background objects like soil. This ensures that only the plant's canopy, including diseased areas, is analyzed. The results ofthese experiments clearly demonstrate that techniques based on the fusion of measurements from different optical sensors have great potential for developing tractor-based systems for disease detection in the field.

8. Plant Viral Disease Detection: From Molecular Diagnosis to Optical Sensing Technology

Optical sensing technologies in plant viral disease detection work by capturing data (like spectral or imaging information) and using mathematical models to interpret it. These models help predict the presence of diseases by comparing the sensed data with known ground-truth data, such as lab tests or visual assessments from experts. The process involves collecting the data, processing it, and then using models—often machine learning or statistical methods—to make predictions. Techniques like **Raman spectroscopy**, **NMR**, and **optical coherence tomography (OCT)** are also used to detect virus-induced changes in plants at a molecular or structural level. Machine learning, especially using **convolutional neural networks (CNNs)**, has become popular for analyzing images and detecting diseases. Models trained on thousands of annotated images, such as those from **UAV-based RGB imaging**, have demonstrated high accuracy in identifying plant diseases, making it a promising approach for automated, real-time detection. Molecular diagnostics rely on prior knowledge of the virus's genetic sequence. If a new or mutated viral strain emerges, these methods may fail to detect it.Development of broad-spectrum molecular tests or metagenomic sequencing approaches that can identify unknown or newly mutated viruses.

9 DL model generalization can be improved due to the use of RGBA images for background removal and augmentation of different data types. Then it can be used for developing field-deployable disease management systems under diverse environmental conditions.

The lack of diversity in image conditions can lead to misleading performance metrics when applied to actual field scenarios.To address this issue, a new dataset called PlantDisease was created. This dataset includes nearly 80,000 images from 12 different plant species, captured under various real-world conditions, including different weather patterns and lighting. The images also feature a mix of backgrounds, with some focusing on single leaves while others show multiple leaves, both healthy and diseased.The introduction of this dataset aims to provide a more realistic training ground for plant disease detection models, enabling them to better generalize to practical situations. Furthermore, all images in the PlantDisease dataset were manually labeled and verified by agricultural experts, enhancing the dataset's reliability and ensuring high-quality annotations. This makes it one of the largest labeled datasets available for plant disease detection, offering a crucial resource for improving model performance in real agricultural contexts.

ANIMAL-DISEASE PREDICTION

Recent advancements in veterinary diagnostics have utilized deep learning to enhance the classification of skin diseases in dogs. This study employed multispectral imaging and Convolutional Neural Networks (CNNs) to classify skin conditions, focusing on bacterial dermatosis, fungal infections, and hypersensitivity. The architectures explored included ResNet50, InceptionV3, DenseNet121, and MobileNetV3Small, all implemented using TensorFlow.

A dataset of 95 images was augmented to increase variability, using resizing, rotation, and translation techniques. The models were trained on this augmented dataset, balanced for binary classification tasks. Performance metrics such as accuracy and AUC were used to evaluate model effectiveness, with the study successfully developing models capable of distinguishing between diseased and non-diseased skin.

This research demonstrates the potential of CNNs, especially with multispectral imaging and data augmentation, for improving veterinary diagnostics, offering a pathway for automated disease detection in animal healthcare

In the field of automated disease detection, recent studies have explored deep learning techniques for classifying Foot and Mouth Disease (FMD) in cattle. This study employed popular Convolutional Neural Network (CNN) architectures, including AlexNet, GoogleNet, and ResNet, to classify FMD-affected and healthy cattle. Various data augmentation techniques, such as rotation, shear, zoom, and brightness adjustments, were applied to enhance the dataset's variability. Transfer learning further boosted model performance, especially given the dataset's limited size.

The results showed that **GoogleNet** outperformed the other architectures, achieving an accuracy of 95%, sensitivity of 96%, and specificity of 93%. **ResNet** and **AlexNet** followed closely, with accuracies of 92% and 91%, respectively. These findings suggest that deep learning, particularly when leveraging transfer learning and data augmentation, offers promising potential for FMD detection in livestock, contributing to effective disease control and prevention.