

Research Paper

Advancements in Plant Disease Detection: Integrating Machine Learning, Image Processing, and Precision Agriculture

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Abstract: - The agricultural sector's pivotal role in India's economy, contributing approximately 15% of the GDP, is underscored, with a focus on the transformative impact of artificial intelligence (AI) technologies such as expert systems, language processing, speech recognition, and machine learning. These technologies have not only enhanced agricultural productivity but also responded to global challenges like population growth, increased food demand, and environmental shifts. Amidst the ongoing pandemic, AI, Machine Learning (ML), and the Internet of Things (IoT) emerge as critical tools revolutionizing the agricultural economy. Furthermore, the detrimental effects of disease outbreaks on agriculture and the national economy are emphasized, necessitating early detection for effective mitigation. While manual disease identification is labor-intensive and error-prone, transitioning to automated procedures presents an efficiency improvement. This paper presents an automated approach for the classification and detection of plant diseases through a dedicated application, addressing a pressing need in modern agriculture.

Keywords- Agriculture, Artificial Intelligence, Disease Detection, Automation, Economic Impact

1. Introduction

Agriculture has long been the backbone of India's economy, contributing significantly to its Gross Domestic Product (GDP). Accounting for approximately 15% of the nation's GDP, the agricultural sector plays a vital role in the country's economic stability and growth. However, this critical sector has not been immune to the rapid changes and challenges brought about by the modern world. In recent years, discussions about the future of agriculture have increasingly centered on one key theme: automation, specifically, the integration of artificial intelligence (AI) technologies into agricultural practices.

The advent of AI has ushered in a new era for agriculture, transforming not only the quantity of agricultural production but also its quality. Expert systems, language processing, speech recognition, and machine learning are just a few examples of AI approaches that have revolutionized the agricultural landscape. These technologies have come to the forefront in response to a complex set of factors, including the ever-increasing global population, the surging demand for food, and shifts in environmental conditions and water availability. In this

introduction, we delve deeper into how these technological innovations have reshaped the agricultural sector and explore their implications for India's economy.

The global population is on an inexorable rise, and with it, the demand for food continues to surge. To meet this escalating demand, agriculture must undergo a profound transformation. Traditional farming practices, while deeply rooted in tradition, may no longer suffice. Here, AI and its subfields like Machine Learning and the Internet of Things (IoT) emerge as powerful allies. These technologies empower farmers with data-driven insights, enabling them to make informed decisions about crop management, resource allocation, and pest control. Through AI-powered predictive analytics, farmers can anticipate changes in weather patterns, adapt planting schedules, and optimize irrigation, ultimately increasing crop yields and food production efficiency.

The COVID-19 pandemic has underscored the critical role of agriculture in sustaining populations and economies. Amid lockdowns and supply chain disruptions, the reliability of the food supply became a global concern. In this challenging context, AI, ML, and IoT have stepped to



the forefront of agricultural resilience. These technologies have enabled remote monitoring and management of crops and livestock, reducing the need for physical labor and ensuring the continuity of food production during times of crisis. The ability to remotely control and monitor agricultural processes has not only ensured food security but also protected the livelihoods of countless farmers.

One of the most pressing threats to agriculture, and by extension, the national economy, is the constant menace of plant diseases. Disease outbreaks can severely impact both the quality and quantity of agricultural goods. In this context, the importance of early disease detection cannot be overstated. Recognizing the need to address this issue, modern agriculture has increasingly turned to technology for solutions. Large-scale agricultural monitoring now includes the proactive search for signs of plant diseases. The goal is to detect infections early, minimizing their impact and preserving crop yields.

However, traditional methods of disease identification and management are fraught with challenges. Manual disease identification, reliant on the trained eyes of professionals, is labor-intensive, prone to errors, and necessitates an in-depth understanding of plant pathogens. Transitioning from these manual methods to automated procedures is a substantial hurdle for many farmers. Yet, the advantages of automation are undeniable. Automated disease detection systems not only reduce the risk of misdiagnosis but also enhance the efficiency of disease management. By swiftly identifying and isolating infected plants, automated systems prevent the spread of diseases, ultimately safeguarding crop yields and the national food supply.

In the forthcoming sections of this research paper, we present a comprehensive exploration of the automated approach we have developed for classifying and detecting plant diseases. This approach leverages the power of AI and machine learning through a dedicated application designed to address the critical need for timely disease detection in modern agriculture. By doing so, we aim to contribute to the ongoing conversation about the pivotal role of technology in transforming agriculture, ensuring food security, and bolstering the economy.

In summary, this introduction provides an overview of the significance of the agricultural sector in India's economy and the transformative impact of AI, ML, and IoT on modern agriculture. It also underscores the importance of early disease detection and sets the stage for a deeper exploration of the automated disease detection approach presented in this research paper.



Figure 1 : Major Applications of AI in Agriculture.

2. Literature Survey

The food and agricultural industries stand as pillars of global importance, serving as the lifeblood of economies and sustenance for populations worldwide. In this context, the fusion of cutting-edge technologies from the realm of artificial intelligence (AI) has emerged as a transformative force, enabling the agricultural sector to meet evolving challenges and opportunities. Among the AI branches, computer vision, machine learning, and image processing hold pivotal roles, ushering in a new era of innovation and efficiency.

The convergence of AI and the Internet of Things (IoT) has paved the way for data-driven decision-making in agriculture. IoT devices deployed in the agricultural landscape are instrumental in collecting and transmitting invaluable information throughout the farming lifecycle, spanning pre-production, production, processing, and transportation phases. These devices, through data acquisition, enable critical tasks such as estimating crop yields, detecting irrigation leaks, forecasting weather conditions, and ensuring product quality. They empower farmers with the ability to make informed choices, optimize resource allocation, and enhance agricultural productivity.

Machine learning, a subset of AI, emerges as a formidable ally in the agricultural domain, particularly in the realm of precision agriculture. Machine learning techniques facilitate the identification of objects within agricultural fields, a crucial aspect of precision agriculture. The impact of these applications is exemplified by Treboux and Genoud's work, achieving an impressive 94.27 percent object recognition rate through machine learning methodologies. Machine learning algorithms equip computers with the ability to acquire knowledge about specific farmland characteristics, regional farming patterns, and various plant and crop types. This knowledge acquisition occurs through both supervised and unsupervised learning, where datasets are either pre-defined or unstructured. Armed with this knowledge, machines can monitor and predict vital environmental factors like soil moisture, crop production, and disease outbreaks.

Furthermore, machine learning finds utility in classifying agricultural datasets by soil and land types, aiding farmers in selecting the most suitable crops for their specific needs. Classification techniques like random forests, naive Bayes, and K-means are instrumental in predicting optimal crops for diverse regions, contributing to resource conservation and cost-effectiveness.

The critical task of disease detection in plants is another realm where machine learning has demonstrated exceptional capabilities. Algorithms such as support vector machines (SVM) and k-nearest-neighbor (KNN) have reported high accuracy rates ranging from 90% to 97% in disease detection studies, making them prominent contenders in the classification domain. The choice of machine learning algorithms is influenced by the nature of the data and the learning process, distinguishing between supervised and unsupervised classifications.

Machine learning encompasses various types of algorithms tailored for specific tasks. Classification algorithms, for instance, enable the categorization of data into distinct groups, while regression techniques predict continuous or time-series data. Unsupervised learning techniques, on the other hand, navigate unstructured datasets, teaching models to recognize patterns for diverse applications, from facial recognition to object identification.

A plethora of research endeavors has advanced the synergy of image processing and machine learning in agricultural contexts. For instance, Anand H. Kulkarni et al. achieved remarkable plant disease detection accuracy of up to 91% through the deployment of image processing techniques such as the Gabor filter coupled with artificial neural network (ANN)-based classification. Similarly, F. Argenti et al. expedited classification processes through supervised training and maximum likelihood techniques.

Innovations extend to low-level image segmentation as well. P. Revannah et al. harnessed edge detection techniques like the Sobel and Canny filters to isolate affected areas and significantly improved the state-of-the-art algorithm's performance. Tushar H. Jaware et al. introduced an enhanced k-means clustering method to address low-level picture segmentation challenges. These advancements are vital for precise disease identification and localized treatment.

Moreover, the Spatial Gray-Level Dependence Matrix (SGDM) technique, as employed by Sanjay B. Dhaygude et al., extracted statistical texture information from RGB images, converting them into Hue Sensitivity Value (HSV) color space representation for improved accuracy. Meanwhile, Mokhled S. Al-Tarawneh explored the application of fuzzy c-means and k-means clustering in olive leaf spot disease detection, culminating in a comparative analysis to enhance image quality and disease identification.

Textural cues have also been employed for potentially hazardous area identification, as suggested by S. Arivazhagan et al. Their SVM-based algorithm, tested across ten different plant varieties, achieved an impressive accuracy rate of 94.74%, exemplifying the potential for machine learning in agricultural risk assessment.

This literature survey illuminates the diverse landscape of AI and machine learning applications in agriculture, encompassing data-driven decision-making, precision farming, disease detection, and image processing. The following sections of this research paper delve deeper into these innovative approaches, shedding light on their practical implications and contributions to the agricultural sector's growth and resilience.

3. Methodology

Accurate retrieval and meticulous evaluation of data related to plant diseases and morphological characteristics from foliar images are crucial processes. Machine Learning plays a pivotal role in the thorough investigation and diagnosis of leaf diseases. Figure 2 illustrates the workflow employed for leaf disease identification, offering insights into the diverse methodologies, including computer vision and artificial intelligence, utilized by the researchers for disease detection.

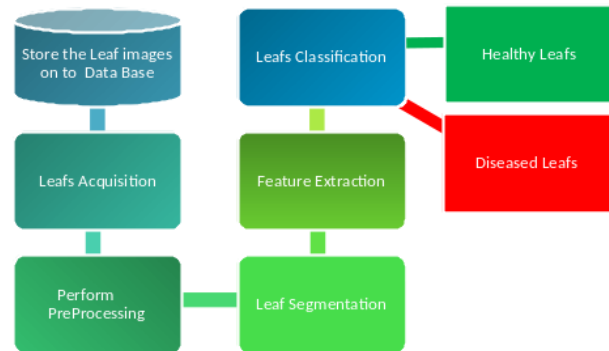


Figure 2: Proposed methodology

The Overall methodology from figure 2 is as follows:

The initial step in disease diagnosis involves the collection of images, with digital cameras and imaging systems serving as viable options for obtaining the necessary imagery. When dealing with raw photos, it is imperative to perform noise reduction. Subsequently, the 'image pre-processing' phase entails adjustments to contrast and brightness to enhance image clarity and eliminate distracting distortions. To further mitigate noise, a common technique involves applying a blurring function like the Gaussian filter. The following phase, known as 'picture segmentation,' separates the main subject from the background and isolates the Region of Interest (ROI) to emphasize critical details. Feature extraction, the fourth stage, unveils pertinent data and specifics within the image. Notably, leaf characteristics crucial for crop diagnosis encompass shape, texture, and color, forming the basis for constructing a feature vector that feeds into the classifier. This vector enables object differentiation and categorization. Classification represents the final step, but it's essential to recognize that not all classifiers are universally effective. The feature vector generated in the fourth phase aids the classifier in categorizing images into distinct classes, a task executed through a dual process of training and testing. Performance improvement often results from increasing the quantity of training sets employed during the training phase. It is imperative to emphasize the need for expedited decision-making, swiftly determining the crop's health status based on its species. The comprehensive overview of this process unfolds as follows:

3.1 Image acquisition & Preprocessing

First, a crucial step involves capturing high-quality digital leaf photographs, capturing leaves from various angles and distances. The organization of these images within the database depends on the intended purpose, with the algorithm's efficacy directly linked to the image database's quality. The efficiency of the subsequent

classifier is profoundly influenced by the caliber of these images.

Secondly, the collected image data undergoes a refinement process, known as pre-processing, aimed at eliminating noise and other artifacts while enhancing essential features before they enter the core processing and analysis stages. This pre-processing encompasses tasks like image augmentation, segmentation, and color space conversion. In particular, RGB leaf photos undergo a transformation into an alternate color space representation known as Hue Saturation Value (HSV). Unlike RGB, which describes colors, HSV is a model for creating and analyzing colors. Within this model, 'hue' characterizes the fundamental color property in its purest form, while 'saturation' quantifies the contribution of pure white light to the color's hue, determining its intensity. Following color space conversion, the 'hue' component is retained for further analysis, while 'saturation' and 'value' are removed from the dataset, as they do not contribute substantively. Notably, many widely-used JPEG images employ color spaces rooted in the Ycbr system, consisting of a luminance component (Y) and two color constituent signals (cb and cr). This Ycbr color space effectively accounts for the impact of additional color components on RGB, making it a preferred choice for image compression processes.



Figure 3: sample of the Plant Village dataset's leaf photos, which depict every possible Crop-disease combination.

3.2 Image Segmentation

Image segmentation is a fundamental technique in digital image processing, serving as the basis for both feature extraction and pattern identification. Various image segmentation methods are available, and we will explore a few of them below.

Region Based: Region-based segmentation involves clustering pixels associated with an object. This method ensures that the segmentation detection region is contiguous, eliminating gaps that may occur when dealing with edge pixels. It determines segmentation boundaries and checks the relevance of at least one pixel in each stage. After recognizing texture and color shifts, edge flow is

transformed into a vector, upon which segmentation is performed based on identified edges.

Edge based: Edge-based segmentation utilizes edge detection methods to identify segmentation borders. Common edge detection methods include Range, Log, Canny, Sobel, Laplacian, and Bob. These methods aim to locate break lines in an image, which are then used for classification, often involving support vector machines with fixed and adaptive features.

Threshold based: Threshold-based segmentation represents a straightforward sub-grouping approach. In this method, threshold values extracted from an image's edge histogram are used for segmentation. The precision of edge detections significantly influences the accuracy of the threshold. Compared to other segmentation methods, thresholding requires less computational effort but may be less suitable for complex images. Refer to Figure 4 for an example of a segmented image.

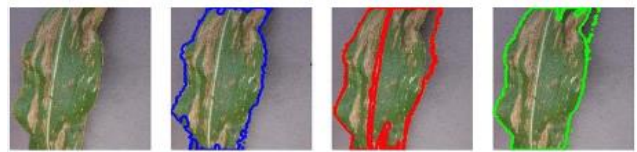


Figure 4: Segmented image

3.3 Feature extraction

The segmentation process is succeeded by the elimination of the affected region. Subsequently, the next step involves the extraction of meaningful attributes to determine the significance of a sample. These image attributes typically encompass elements such as hue, contour, and texture. Currently, researchers are placing a significant emphasis on analyzing the texture of plant leaves as a means of classifying various plant species. Textural properties play a pivotal role in categorizing plant diseases into their respective classes. As evident, there exist multiple approaches to the feature extraction process.

3.3.1 Texture analysis methods

In the realm of image analysis, textures represent patterns formed by the non-uniform distribution of pixel intensities within an image. These patterns provide valuable insights into the spatial relationships within image materials and are integral to characterizing texture. Texture analysis relies on several key characteristics, including homogeneity, consistency, volume, linearity, orientation, roughness, coarseness, stage, and frequency. Texture power classification typically encompasses four main methodologies: statistical, structural, fractal, and signal processing.

Statistical Analysis:

Statistical methods for texture extraction involve a range of techniques, including grayscale histograms, co-occurrence matrices, auto-correlation characteristics, and runtime matrices. These statistical approaches provide valuable quantitative insights into texture patterns.

Structural Analysis:

Texture structural models operate on the premise that textures are composed of various texture primitives. Structural texture analysis involves two primary processes: the extraction of texturing elements and the deduction of placement rules. Potential structural techniques encompass two-dimensional wavelet transform and the Gabor transform.

Fractal Analysis:

Many naturally occurring surfaces exhibit statistical characteristics of roughness or self-similarity across different scales, commonly referred to as fractals. Modeling these textural features using fractal methodologies has become a prevalent and practical practice in the field of image processing.

Signal Processing:

Texture's inherent qualities make it well-suited for analysis through signal processing techniques. Various filters are employed in this context, encompassing spatial domain filters, Fourier domain filters, and the application of the two-dimensional Gabor function.

Incorporating these diverse approaches, texture analysis provides a comprehensive framework for understanding and quantifying the intricate patterns and spatial relationships that exist within images.

3.4. Image Classification:

Texture classification, based on their distinctive features, employs various established methodologies:

(i). K-Nearest Neighbor (K-NN):

The K-Nearest Neighbor classifier evaluates the proximity of a point to different candidate categories. It calculates the distance from the query sample to each training sample and identifies the closest training sample. The classification decision is made based on this proximity, where the 'k' closest neighbors can influence the outcome.

(ii) Radial Basis Function (RBF):

The Radial Basis Function (RBF) relies on the simple premise that its value depends solely on the distance from the origin, with Euclidean distance being a common choice. In RBF networks, the distance between an input vector and prototype vectors activates hidden units, making it a valuable tool for texture classification.

(iii) Artificial Neural Networks (ANN):

Artificial Neural Networks (ANNs) represent a prevalent machine learning technique. In Multilayer Perceptron (MLP) ANNs, weight updates occur through backpropagation during training. Recent developments have introduced alternative neural network architectures into the domain of texture categorization:

- Probabilistic Neural Network (PNN): Derived from RBF networks, PNN is a parallel distributed processor that exhibits an inherent ability to encode experiential knowledge. Comprising input, pattern, summation, and output layers, PNN's operations are organized based on kernel discriminant analysis, a statistical method.

- Convolutional Neural Network (CNN): CNNs, equipped with convolutional input layers, possess autonomous feature extraction capabilities from images. This characteristic allows for feature extraction and classification within a unified architectural framework.
- Backpropagation Network: A basic Backpropagation (BP) network consists of input, hidden, and output layers interconnected via weighted connections. BP networks adapt by iteratively adjusting these weights to minimize the sum of squared errors relative to the desired output. While widely used in feedforward network training, BP networks lack built-in novelty detection and require pre-seen data for training.

(iv) Support Vector Machine (SVM):

Support Vector Machines (SVMs) represent a relatively recent innovation in the realm of machine learning, serving as powerful non-linear classifiers. SVMs find extensive application in texture categorization and various other pattern recognition tasks. SVMs are inherently binary classifiers, striving to maximize the margin from the hyperplane. Support vectors, strategically placed near the decision boundary, dictate the positioning of the hyperplane. To address multiclass classification challenges, one-versus-all and other two-class SVMs can be employed effectively.

The classification results for each method are illustrated in Figure 5, offering insights into the performance of these diverse classification approaches.



Figure 5: Normal and Abnormal Leaves classification after final phase

4. Result and Analysis

4.1 Dataset Description

Within our dataset, we have carefully curated 76,915 photographs of plant leaves, encompassing a diverse range of 55 unique label classes. Our primary goal is to predict the specific crop and disease combination associated with each leaf label, relying solely on the image of the plant leaf itself as the label. To ensure compatibility across various methodologies discussed in this study, we have consistently downscaled all images to a resolution of 512 by 512 pixels.

In this research, we conducted our experiments using three distinct iterations of the comprehensive Plant Village dataset. These iterations include the original color version, a grayscale variant, and a version in which leaves have been meticulously categorized to eliminate potentially biased background details introduced during the dataset's initial data collection process.

To streamline the analysis process, we employed a custom script designed to automate the segmentation process. This script leverages masks generated from both Lab and HSB color spaces to assess differences in hue, brightness, and saturation across various regions of the images. Additionally, we addressed color casts that were particularly prominent within specific subsets of the dataset during this preprocessing stage, further enhancing the dataset's fairness.

It's important to note that the dataset's size, consisting of 76,915 photos, ensures the robustness and representativeness of our analysis. The results of leaf categorization and disease detection evaluations for this dataset are presented in Table 1, reflecting the outcomes of our experiments across this substantial collection of plant leaf images.

The software requirements for the IoT system are also specific to the features that are implemented in the system. For example, if the system is able to track the location of the vehicle, the software requirements will need to include the code for the tracking functionality.

The software requirements for the IoT system are an important part of the system design process. The software requirements must be carefully specified so that the system can be implemented correctly.

Table 1: Results of Various Algorithms

Step	Crop	Classification Algorithm Used	Validation	Test
Leaves classification	All	K-Nearest Neighbor	93.56	92.45
		Support Vector Machine	98.71	97.68
		Probabilistic Neural Network	94.23	93.14
		Convolution neural network	92.51	91.53
Disease Classification & Detection	All	K-Nearest Neighbor	94.56	93.54
		Support Vector Machine	98.56	99.51
		Probabilistic Neural Network	97.54	95.24
		Convolution neural network	99.52	99.26

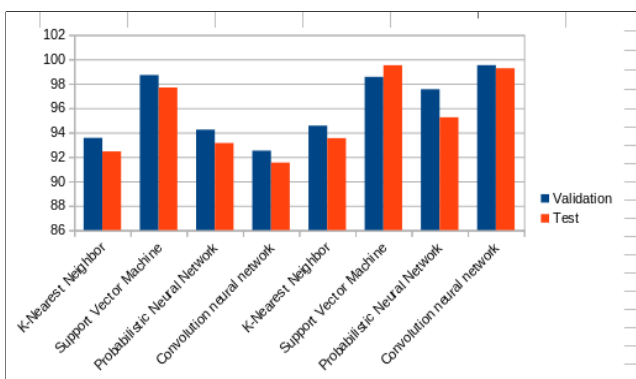


Figure 6: Evaluated Results of Various Algorithms

The outcomes of our system's evaluation are presented in Table 1 and Figure 6. We deployed four distinct classification algorithms to discern between healthy and infected leaves based on observed symptoms. Our analysis, as depicted in Table 1 and Figure 6, highlights the notable performance of SVM in leaf classification during

validations and tests. Conversely, CNN excelled in disease classification and detection. Impressively, all remaining models achieved accuracy rates exceeding 92%, underscoring the effectiveness of AI-based machine and deep learning models in disease detection and classification.

5. Conclusion

Crop diseases pose significant challenges to the agricultural industry, necessitating early detection to mitigate their severity and prevent their spread on farms. This study has presented a comprehensive overview of recent advances in the field, summarizing cutting-edge research from the past few years. We have explored various methods for disease identification, with a particular focus on the application of artificial intelligence-based techniques in machine learning and deep learning across diverse plant species.

Key methods such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and K-means clustering have emerged as prominent tools for diagnosing plant diseases, enabling the differentiation between healthy and diseased plant leaves. Recognizing that both image quality and method optimization can significantly impact results, our research emphasizes the importance of tailoring these approaches to specific plant leaf diseases. Moreover, the automation of disease identification for continuous field monitoring is a critical aspect of this work.

Through a rigorous evaluation, encompassing all four classification methods, our findings have showcased the impressive potential of these techniques. SVM exhibited a remarkable 98% success rate in leaf classification, while CNN achieved an exceptional 99% success rate in disease detection. These results underscore the promising prospects of artificial intelligence-based approaches for enhancing disease identification and monitoring in agriculture, offering valuable insights for future research and practical applications.

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