Crop And Disease Detection: A Comprehensive Survey

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I. ABSTRACT

Crops serve as the lifeblood of agriculture, playing a pivotal role in agricultural fields. However, the occurrence of various diseases on plants poses a significant challenge, leading to reduced productivity and affecting the overall quality of the yield. Plant diseases are a big problem for crops, causing lower productivity and poor quality. Detecting these diseases early is crucial, but current methods are tough for farmers. We need a simpler and automated way to find these diseases early on. Automatic disease identification proves to be instrumental in easing the cumbersome process of screening diseases in extensive crop farms. The principal objective of this survey is to adeptly identify leaf diseases in various crops such as Arhar, Cotton, Gram, Groundnut, Maize, Moong, Paddy, Rapeseed and Mustard, Sugarcane, Wheat, with minimal processing time, thereby ensuring a robust output. This approach seeks to streamline the identification process, ultimately leading to savings in terms of manpower, financial resources, and time. The innovative methodology presented in this survey encompasses sequential steps, including Pre-Processing, Thresholding, Sobel Filter, Morphological Dilation, and Region of Interest (ROI) Extraction.

II. INTRODUCTION

Agriculture is the backbone of global food production, and ensuring the protection of crops against diseases is paramount for sustainable agriculture. This survey paper aims to explore and critically assess various technologies and methods employed in crop and disease protection, analyzing their advantages and disadvantages. Agriculture holds a pivotal role in India's economy, serving as a primary source of livelihood. Similar to human health, plants encounter diseases that hinder their normal growth. Afflictions can manifest in various plant parts such as leaves, flowers, fruits, and roots, with the vast diversity of crops contributing to a substantial array of diseases. Consequently, accurately diagnosing these diseases poses challenges for pathologists due to their complexity and the sheer number of cultivated plants.

The precise and timely identification of plant diseases is crucial for safeguarding crops against both quantitative and qualitative losses. Unfortunately, many farmers lack sufficient knowledge about effectively detecting plant diseases. Manual identification of diseases with the naked eye is not only time-consuming but also demands continuous monitoring, resulting in less accurate assessments. The introduction of automated systems for disease identification not only minimizes human effort but also enhances accuracy. Such automated solutions offer significant benefits to farmers who often possess limited knowledge about plant diseases.

In the contemporary era, extensive research is underway in the realm of machine learning, offering effective applications in health monitoring and the identification of plant diseases. This paper focuses on diseases affecting plant leaves, exploring several machine learning approaches proposed by different researchers. These techniques utilize color, shape, texture features, and deep learning models to detect and diagnose diseases in plant leaves.

III. LITERATURE REVIEW

In 2007 Tellaeche et al. [3] proposed two mechanisms: segmentation of images and decision making. To divide cells from the image as low-level parts, image segmentation incorporates simple image processing techniques. 2 area-based attributes computing the relationships between crop rows and weeds define each part. A hybrid supervisory methodology decides, from these properties, whether or not a cell must be sprayed. The decision is depending on the merger of two well-known classifiers (SVM and FM) under the Bayesian system. To recognize cucumber crop leaf disease based on IP and SVM was introduced in 2008 [1]. To reduce noise from the obtained cucumber disease leaves color images, the vector median filter was initially used. The color picture of the cucumber disease spot on the leaf was derived from the texture, shape and color characteristics. The system used SVM and neural networks classifiers. Shape feature gives more accuracy than the texture and color feature give faster results. The results showed that SVM performance is better than neural networks. Linear kernel of SVM gives better results than polynomial, radial basic, and sigmoid functions.

In 2015, S. Khirade et al. [7] addressed the challenge of detecting plant diseases through the application of digital image processing techniques and backpropagation neural networks (BPNN). The authors presented various methods for identifying plant diseases based on leaf images. Their approach involved employing Otsu's thresholding, followed by boundary and spot detection algorithms to isolate the infected portions of leaves. Subsequently, they extracted diverse features like color, texture, morphology, and edges for disease classification. The classification task was carried out using BPNN to identify and diagnose plant diseases.

Shiroop Madiwalar and Medha Wyawahare conducted a comprehensive analysis of different image processing methodologies for plant disease detection in their study. The authors specifically investigated color and texture features for disease identification, conducting experiments on a dataset comprising 110 RGB images. The extracted features for classification included the mean and standard deviation of RGB and YCbCr channels, grey level co-occurrence matrix

(GLCM) features, as well as the mean and standard deviation of the image convolved with a Gabor filter. For classification purposes, a support vector machine (SVM) classifier was employed. The authors concluded that GLCM features were effective in detecting healthy leaves, while color features and Gabor filter features proved optimal for identifying anthracnose-affected leaves and leaf spot, respectively. The authors achieved their highest accuracy of 83.34% by utilizing all the extracted features.

Mohanty et al. [6] proposed a system in 2016 to recognize plant leaf diseases using DL. They built a deep CNN to classify 14 crop varieties and 26 diseases by a dataset of 54,306 images of PlantVillage dataset. They compared various CNN architectures on transfer learning and scratch training. In the case of the colored version of the dataset, the models work better. The limitation is that the classification of single leaves, facing up, in a homogeneous context, is currently limited.

Goncharov et al. [9] to provide the solution for the problem of tiny image databases, the deep siamese convolutional network was created. The identification of the 3 diseases namely Esca, Black rot, and Chlorosis disease on grape leaves had an accuracy of over 90%. Panigrahi et al. [10] the research focused on traditional machine learning techniques for the recognition of maize crop diseases, such as NB, DT, KNN, SVM, and RF. In order to choose the most apt model with the highest precision for plant disease prediction, the aforementioned classification techniques are analyzed and compared. The RF algorithm provides the best results, with 79.23% accuracy. Sagar et al. [11] compared five different architectures: ResNet50,VGG16, InceptionV3, Inception, ResNet, and DenseNet169.They discovered that the best result on the test set was ResNet50 with 94% accuracy, it uses skip connections using a residual layer archive. They computed performance by precision, accuracy, recall and F1 score.

IV. RESEARCH METHOD

The model architecture for detecting and classifying crop leaf diseases based on visual symptoms involves five essential steps: image acquisition, image preprocessing, image segmentation, feature extraction, classification.

1) *Image Acquistion:*

This constitutes the initial phase of crop leaf disease detection and classification. The objective at this stage is to assemble and ready the image dataset intended for subsequent processing. This involves capturing images either on-site in real-time conditions or under controlled settings using mobile phone cameras, digital cameras, drones, or UAVs.

2) *Image Preprocessing*:

Effective image preprocessing is crucial for achieving improved results. Employing color transformations was essential to eliminate noise, while resizing techniques were applied to reduce the size of images captured by digital cameras, aiding in memory size reduction. Commonly utilized preprocessing techniques in this literature involve operations such as cropping leaves from acquired images, color transformations, rescaling, background removal, image enhancement, flipping, rotating, shearing, and image smoothing

3) *Image Segmentation:*

In crop leaf disease detection and classification, image segmentation is a crucial component that divides the image into distinct parts or zones. This process investigates the image data to extract valuable information for subsequent feature extraction. Image segmentation can be approached in two ways: one method is similarity-based, while the other relies on discontinuities.

4) *Feature Extraction:*

Feature extraction in plant disease detection involves identifying key elements like shape, color, and texture from images. These features help differentiate crop diseases based on leaf appearance, color variations, and patterns, enhancing disease recognition.

5) *Classification:*

Two types of classification methods were used to classify crop leaf diseases: Machine Learning and Deep Learning.

Chowdhury et al. [12] proposed a plant disease detection and classification system, it uses transfer learning and deep feature extraction in. The authors were compared the obtained results of VGG16, GoogLeNet, ResNet50 CNN architectures with deep feature extraction by SVM and KNN. Experiment results shown that classification with SVM and ResNet50 given best results (98%) than the remaining combinations. The authors also compared the results of traditional machine learning algorithms i.e. SVM and KNN, SVM shown better accuracy (80.6%) than KNN (71.8%) but it is lesser than the proposed.

V. METHODOLOGIES AND APPROACHES

1) *Data Preprocessing and Feature Extraction:*

Data preprocessing is a critical step in computer vision systems. To enhance precision, background noise is eliminated by converting the RGB image to greyscale, applying a Gaussian filter for smoothening, and utilizing Otsu's thresholding algorithm for binarization. Morphological transformation closes small holes in the foreground. Subsequently, a bitwise AND operation between the binarized and original color image yields the segmented leaf in RGB. Shape, texture, and color features are then extracted, including leaf area, perimeter, mean, and standard deviation of each RGB channel. Green color content is determined by calculating the ratio of pixels with hue intensity between 30 and 70 in the HSV color space. Non-green content is obtained by subtracting the green part from 1.

Following the extraction of color features from the image, we obtained texture features from the grey level co-occurrence matrix (GLCM) of the image.

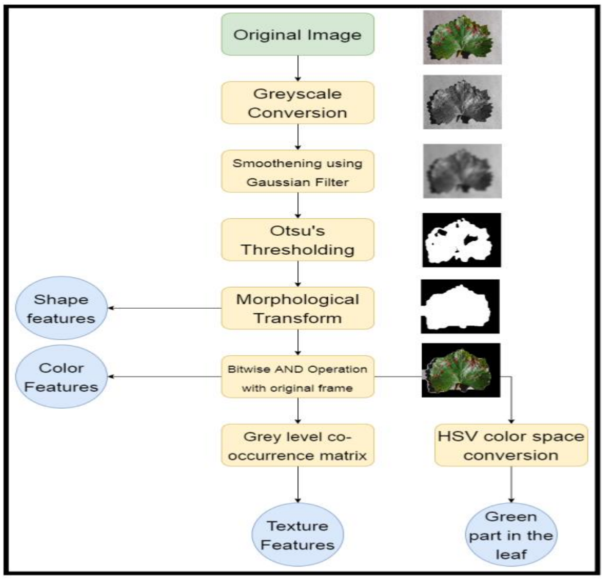

Fig.1 Steps for data preprocessing and feature extraction

The Grey Level Co-occurrence Matrix (GLCM) represents the spatial relationships between pixels in an image. Extracting texture features from GLCM is a conventional method in computer vision. From the GLCM, we derived the following features:

- Contrast
- Dissimilarity
- Homogeneity
- Energy
- Correlation

Following the extraction of features from all images in the dataset, a feature selection task was conducted.

2) Feature Selection:

Feature selection is a crucial step in machine learning, particularly in this project where features are chosen based on their correlation with the target variable, the correlation matrix for the apple dataset reveals a high correlation (1) between the green part of the leaf features (F1 and F2), indicating dependency. To address this, one of the variables (F2) is dropped. Additionally, less correlated features, such as green channel mean, red channel standard deviation, blue channel standard deviation, dissimilarity (f5), and correlation (f8), are excluded to enhance model development for apple disease prediction. Following feature selection, the refined data is input into machine learning classifiers to identify patterns in the dataset.

3) Classification Algorithm:

The classification task employed the Random Forest classifier, a key component of ensemble learning utilizing multiple base estimators [8]. Decision trees are commonly used for higher accuracy, but they can be susceptible to overfitting. To address this, the Random Forest classifier combines multiple decision trees, each trained on different subsets of the dataset, mitigating overfitting and enhancing overall accuracy. The dataset was split into an 80% training set and a 20% test set for model fitting and validation. K-fold cross-validation ensured unbiased accuracy assessment. Metrics such as F1 score, precision, recall, and accuracy were calculated from the test data to evaluate model performance. The ROC curve and confusion matrix were utilized to analyze false positives and false negatives

VI. OVERVIEW OF CROP PROTECTION TECHNOLOGIES

Crop protection is a multifaceted domain encompassing safeguarding plants from pests, diseases, and environmental stressors. Technologies in this realm can be broadly categorized into chemical and biological.

1) Chemical Approaches:

Chemical pesticides have been the cornerstone of crop protection for decades. Their use provides quick and effective solutions, effectively managing pests and diseases. However, the extensive application of chemical pesticides raises environmental concerns, including soil and water contamination, and contributes to the development of pesticide-resistant strains.

2) Biological Approaches:

Biological control methods involve leveraging natural predators or parasites to control pest populations. Beneficial insects, nematodes, and microorganisms are employed to maintain ecological balance in agricultural systems. While these methods are environmentally friendly, their implementation might require more time to show results compared to chemical interventions.

VII. DISEASE PROTECTION TECHNOLOGIES

Diseases pose a significant threat to crop yields, and innovative technologies have been developed to address this challenge. IPM represents a holistic approach that combines various strategies, incorporating chemical, biological, and cultural practices. By integrating these methods, IPM aims to minimize environmental impact while maximizing crop yield. This approach emphasizes a nuanced understanding of the ecosystem to create sustainable, long-term solutions.

1) Resistant Crop Varieties:

Developing crop varieties with inherent resistance to prevalent diseases is a proactive and sustainable approach. This method involves traditional breeding techniques as well as modern genomic tools. For example, the identification and incorporation of resistance genes can fortify crops against specific pathogens. However, the challenge lies in balancing resistance with other desirable traits such as yield, taste, and nutritional content. Ongoing research focuses on identifying and introducing a broader range of resistance genes to enhance crop resilience.

2) Precision Agriculture:

Precision agriculture utilizes data-driven technologies like sensors, drones, and satellite imagery for accurate crop health monitoring. These tools enable real-time insights, early disease detection, and targeted interventions.

Implementation requires substantial investment in technology and user-friendly interfaces, with education and training programs essential for seamless integration into existing farming practices.

3) Genetic Modification:

Genetic modification, notably through CRISPR-Cas9, enables precise enhancement of crop resistance to diseases by introducing or modifying specific genes. This targeted approach addresses susceptibility to pathogens, yielding crops resistant to viruses and fungi. Public concerns about GMO safety persist, necessitating balanced regulatory frameworks for innovation and food supply safety. Ongoing efforts aim to create genetically modified crops addressing multiple disease challenges simultaneously for a comprehensive solution

4) Remote Sensing And Imaging Technologies:

Remote sensing technologies, including hyperspectral imaging and thermal imaging, offer non-invasive methods to assess plant health. Hyperspectral imaging can identify subtle changes in plant pigments and biochemical composition associated with diseases. Thermal imaging detects variations in plant temperature, highlighting potential stress or infection. Integrating these technologies into disease monitoring systems enhances the precision of diagnostics and facilitates targeted disease management.

VIII. CHALLENGES AND GAPS

Diseases pose a significant threat to crop yields, and innovative technologies have been developed to address this challenge. IPM (Integrated Pest Management) represents a holistic approach that combines various strategies, incorporating chemical, biological, and cultural practices. By integrating these methods, IPM aims to minimize environmental impact while maximizing crop yield. This approach emphasizes a nuanced understanding of the ecosystem to create sustainable, long-term solutions.

A nuanced examination of the pros and cons of crop and disease protection technologies is crucial for informed decision-making.

1) Advantages:

- Increased Crop Yields: Adoption of modern technologies often leads to higher yields, addressing the global demand for food.
- Efficient Resource Utilization: Precision agriculture and integrated approaches optimize the use of resources such as water and fertilizers.
- Minimized Environmental Impact: Biological approaches and integrated pest management contribute to reducing chemical inputs and environmental pollution

2) Disadvantages:

- Environmental Pollution: Chemical approaches contribute to soil and water pollution, impacting ecosystems.
- Pesticide-Resistant Pests: Overreliance on chemical pesticides can lead to the development of resistant pest populations.
- Harm to Non-Target Organisms: Chemical pesticides may harm beneficial insects and other non-target organisms.

IX. LIMITATION AND FUTURE RESEARCH DIRECTION

In reviewing the landscape of crop leaf disease detection systems based on visual symptoms, several key limitations have been identified. These challenges encompass dataset constraints, issues with dataset development, algorithmic considerations, and resource intensiveness.

1. Limited Datasets:
   - PlantVillage is the primary public dataset, but it lacks diversity for commercial crops like chili.
   - Some authors have proprietary datasets, hindering result comparisons.
2. Dataset Development Challenges:
   - Issues in image acquisition and preprocessing include uneven illumination and cluttered backgrounds.
   - Neglect of real cultivation conditions and unused plant parts for disease detection.
3. Algorithmic Considerations:
   - Need for applying ensemble algorithms, hyperparameter tuning, and diverse pooling operations [19].
4. Resource Intensiveness:
   - Deep learning-based prediction systems demand substantial resources [25].
   - Significance of developing squeeze models for application in mobile phones, drones, UAVs, and robots.

Future work involves developing real-time datasets with extensive images and diverse classes of plant diseases, integrating crop disease datasets with location, weather, and soil data for smart agriculture, and enhancing prediction systems for large-scale horticultural fields.

Anticipating future trends is vital for the continuous improvement of crop and disease protection technologies.

1) Precision Agriculture Advancements:

Continued advancements in precision agriculture promise to revolutionize disease monitoring and management. Integration of artificial intelligence (AI) and machine learning algorithms can analyze vast amounts of data generated by sensors and drones. AI-powered systems can provide farmers with predictive models for disease outbreaks, allowing for proactive measures. Additionally, the development of autonomous machinery and robotics holds the potential to further enhance the efficiency of precision agriculture. These technologies can perform tasks such as seeding, spraying, and harvesting with high precision, reducing labor requirements and operational costs.

2) Sustainable Approaches:

The future of crop protection lies in developing sustainable technologies that not only minimize environmental impact but also address societal concerns regarding food safety. Research into organic farming methods, agroecology, and regenerative agriculture practices is gaining momentum. These approaches emphasize soil health, biodiversity, and ecosystem resilience, aiming to create farming systems that are both productive and environmentally friendly. Adoption of sustainable practices, however, faces challenges such as the need for education and support for farmers transitioning from conventional methods and the potential trade-offs between sustainability and short-term economic gains.

3) Digital Agriculture and Connectivity:

The increasing connectivity of rural areas and the rise of the Internet of Things (IoT) in agriculture contribute to the evolution of digital agriculture. Smart farming technologies, including connected sensors, smart irrigation systems, and real-time data analytics, enable precise and data-driven decision-making. The integration of digital technologies can improve resource efficiency, optimize crop management, and enhance overall farm productivity. However, challenges such as the digital divide in rural areas, data privacy concerns, and the high initial costs of implementing digital solutions need to be addressed to ensure widespread adoption.

4) Climate Change Resilience:

As climate change continues to impact global weather patterns, agriculture faces increased uncertainty and risks. Future trends in crop and disease protection will likely include the development of crops resilient to extreme weather conditions, such as drought-resistant varieties and those adapted to changing temperature patterns. Additionally, innovations in predictive modelling and climate-smart technologies will play a crucial role in helping farmers adapt to the challenges posed by climate change. Research and investment in climate-resilient agricultural practices are essential to ensure food security in the face of environmental uncertainties.

X. CONCLUSION

Rapid advancements in crop and disease protection technologies offer diverse solutions for sustainable agriculture. Striking a crucial balance between increased productivity and environmental conservation is imperative. This survey provides a comprehensive overview of the current landscape, underscoring the need for ongoing research, responsible implementation, and adaptive regulatory frameworks in agricultural practices. The journey toward sustainable agriculture necessitates collaboration among researchers, policymakers, and stakeholders to address emerging challenges and seize opportunities for a resilient and food-secure future. Additionally, the process of identifying crop leaf diseases is outlined in five steps: image acquisition, pre-processing, segmentation, feature extraction, and classification. The survey delves into methodologies, accuracy, datasets, crop types, image requirements, and classes, emphasizing the importance of integrating computer vision and machine learning in agriculture. Further exploration, real-time disease detection for large-scale yields, and resource-efficient approaches are crucial for advancing sustainable practices in agriculture.

XI. REFERENCES

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