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Image Processing Based Computational Intelligent Methodology for Plant Disease Detection and Classification

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Abstract: This research introduces a novel approach to identifying and categorizing plant diseases by integrating image processing methods with computational intelligence. With the increasing importance of agriculture in ensuring food security, timely identification and precise categorization of plant diseases play a pivotal role in efficient disease control and maximizing crop productivity. Conventional disease detection approaches typically involve manual intervention, leading to subjective interpretation, time inefficiency, and susceptibility to errors. In this research, we harness the power of digital image processing to automate the detection process, providing a rapid and objective means for identifying plant diseases. We utilize cutting-edge image processing algorithms to extract pertinent features from plant images, capturing intricate details associated with various symptoms of diseases. Following this, we apply computational intelligence methods like machine learning and deep learning to classify diseases using the extracted features. Our proposed methodology offers several advantages over conventional approaches. By leveraging computational intelligence, the system can adapt and learn from a vast amount of image data, enhancing its accuracy and robustness in disease classification. Furthermore, the automation of disease detection reduces the dependency on human expertise, enabling scalable and cost-effective solutions for agricultural stakeholders. To validate the efficacy of our methodology, extensive experiments are conducted on diverse datasets encompassing various plant species and disease types. The outcomes exhibit encouraging performance concerning accuracy, sensitivity, and specificity, highlighting the viability of the suggested approach for practical applications in agriculture. In conclusion, this research presents a novel and efficient framework for plant disease detection and classification, merging the capabilities of image processing and computational intelligence. The proposed methodology holds significant promise for revolutionizing disease management practices in agriculture, facilitating timely interventions and ultimately contributing to global food security.

Keywords: *Computational intelligence, Disease classification, Image processing, Machine learning (ML), deep learning (DL), Plant disease detection*

1. Introduction

In recent years, the agricultural sector has witnessed significant advancements in technology, particularly in the realm of digital imaging and computational intelligence. These advancements have opened up new avenues for addressing critical challenges in agriculture, such as plant disease detection and classification. Plant diseases present a significant risk to crop yield and quality, affecting global food security and economic stability. Timely detection and precise classification of these diseases are critical for implementing prompt interventions and mitigating crop losses.

Conventional plant disease detection methods often rely on visual inspection by agricultural experts, which can be subjective and time-consuming, especially for large-scale farming. Moreover, manual inspection may miss diseases in their early stages when intervention is most effective. To overcome these limitations, researchers are turning to automated systems integrating image processing and computational intelligence for more efficient detection and classification.

Image processing offers a powerful means of extracting valuable information from digital images of plants, allowing for the identification of disease symptoms with high precision. By analyzing various features such as color, texture, and shape, image processing algorithms can detect subtle changes associated with different types of plant diseases. Furthermore, computational intelligence techniques, including ML and deep learning, enable the expansion of robust classification models that can learn from vast amounts of image data and adapt to different disease patterns.

Combining image processing with computational intelligence offers tremendous potential to transform practices in managing plant diseases. By automating the detection process, agricultural stakeholders can swiftly identify diseased plants and implement targeted interventions, thereby reducing the spread of diseases and optimizing crop yields. Additionally, these technologies offer scalability and cost-effectiveness, making them accessible to farmers across diverse agricultural settings.

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In this paper, we present an innovative methodology for plant disease detection and classification based on image processing and computational intelligence. We discuss the theoretical foundations of image processing algorithms and computational intelligence techniques employed in our methodology. Furthermore, we demonstrate the practical implementation of our approach through case studies and experimental results, highlighting its efficacy in real-world agricultural settings.

In sum, our study adds to the expanding field of agricultural technology by presenting a holistic framework that harnesses image processing and computational intelligence for effective plant disease management. By fostering ongoing innovation and partnerships, we anticipate a future where cutting-edge technologies play a pivotal role in securing global food supplies and fostering sustainability.

2. Related Work

A multitude of investigations have delved into the utilization of image processing methods for detecting plant diseases. For instance, Zhang and colleagues (2019) pioneered a technique for identifying tomato diseases by analyzing color and texture attributes derived from leaf images. Similarly, Singh et al. (2020) employed image segmentation and feature extraction techniques to classify citrus plant diseases with high accuracy. These studies demonstrate the efficacy of image processing in capturing disease symptoms and making a clear distinction between healthy and afflicted plants.

Computational intelligence techniques, particularly machine learning and deep learning, have gained prominence in agricultural research due to their capacity to scrutinize extensive datasets and derive significant patterns. In a study by Mohanty et al. (2016), convolutional neural networks (CNNs) were employed for automatic identification of plant diseases using leaf images. The approach based on CNNs demonstrated superior performance in contrast to conventional machine learning techniques, showcasing the potential of deep learning in plant disease classification.

Numerous scholars have suggested methodologies that combine image processing with computational intelligence to improve the detection and classification of plant diseases. Barbedo (2019) developed a comprehensive framework combining image processing algorithms with machine learning techniques for identifying soybean diseases. The integrated approach demonstrated robustness against variations in environmental conditions and disease severity levels, highlighting its suitability for practical agricultural applications.

While significant progress has been made in image processing-based methodologies for plant disease detection, several challenges remain. An obstacle in this domain involves acquiring annotated image datasets that cover various plant species and disease types, essential for training robust classification model. Moreover, implementing automated disease detection systems in practical agricultural contexts involves addressing factors like hardware compatibility, scalability, and ease of use.

Recent advancements in sensor technology, including unmanned aerial vehicles (UAVs) and hyperspectral imaging, offer new possibilities for remote and non-invasive monitoring of plant health. Integrating these technologies with image processing and computational intelligence could further enhance the precision and efficiency of plant disease recognition systems. Moreover, the development of mobile applications and cloud-based platforms facilitates the dissemination of information and decision support tools to farmers, empowering them to make informed management decisions. To summarize, the literature review emphasizes the importance of employing computational intelligence methodologies based on image processing for detecting and classifying plant diseases. By leveraging advances in both fields, researchers aim to develop robust, scalable, and providing practical and attainable solutions to tackle the obstacles in plant disease management, thus safeguarding global food security.

A methodology proposed in Zhang, L., Zhang, H., & Xie, W. (2019) for tomato disease recognition using image processing technology. Utilizing color and texture characteristics derived from leaf images aids in identifying diseases, showcasing the effectiveness of employing image processing techniques in detecting plant diseases. Singh, D., Gupta, P., Kumar, P., & Kaur, M. (2020) introduce an automated system for classifying citrus plant diseases using image segmentation and feature extraction techniques. The integration of image processing and machine learning facilitates accurate disease classification, contributing to improved plant health management.

Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016) explore the utilization of deep learning, focusing on convolutional neural networks (CNNs), for detecting plant diseases using image data. Their CNN-based approach exhibits superior performance over traditional machine learning algorithms, underscoring the efficacy of deep learning in plant disease classification.

Barbedo, J. G. A. (2019), discusses the repercussions of plant diseases on crop production and delves into the possibilities presented by digital agriculture and artificial intelligence for disease management. The study proposes a comprehensive framework integrating image processing algorithms with machine learning techniques for soybean disease identification, emphasizing the importance of advanced technologies in agricultural practices.

Table 1. A comparative overview of different methodologies for plant disease detection and classification

Methodology	*Advantages*	*Disadvantages*	*References*
Traditional Image Processing Based Approaches	Simple and interpretable. Well-established techniques. Low computational complexity.	Limited ability to capture complex patterns. Relies heavily on handcrafted features. May require expert domain knowledge for feature design.	[1] [2]
Machine Learning Based Approaches	Ability to learn complex patterns. Can handle large datasets efficiently. Versatile, adaptable to various problems.	Dependence on labeled training data. Performance impacted by quality and quantity of data. Overfitting and generalization issues.	[3], [4], [5]
Deep Learning Based Approaches	Leading performance in various tasks. Automatic feature learning. Can capture intricate patterns and nuances.	High computational requirements, especially for training. Requires large amounts of labeled data. Interpretability can be challenging.	[4], [6], [7]
Hybrid Approaches	Combines strengths of different methods. Improved robustness and generalization. Flexibility to adapt to specific problems.	Increased complexity in integration. May require expertise in multiple domains. Potential computational overhead.	[8], [9], [10]

The use of deep learning techniques are investigated by Mehmood, I., Hussain, M., Baik, S. W., & Lee, Y. S. (2017) for plant disease detection and saliency map visualization. The study demonstrates the effectiveness of deep learning models in identifying diseased regions within plant images, providing insights into the underlying disease symptoms. Table 1 shows different methodologies for image processing based computational intelligent methodology for plant disease detection and classification. Table 1 provides a comparative overview of different methodologies for the detection and classification of plant diseases, highlighting their respective advantages and disadvantages.

Plant diseases represent a substantial risk to worldwide agriculture, affecting crop yield, quality, and food security. Conventional disease detection methods typically involve manual inspection, which is both time-consuming and subjective. However, with the recent progress in image processing and computational intelligence, scholars have investigated novel strategies for automating plant disease detection and classification. This review scrutinizes diverse approaches and technologies employed in this domain, shedding light on their role in improving disease management in agriculture.

Image processing techniques play a crucial role in extracting relevant information from digital images of plants. These techniques encompass processes such as image segmentation, feature extraction, and pattern recognition, enabling the identification of disease symptoms with high precision. Research conducted by Singh et al. (2020) and Noh et al. (2015) illustrates how image processing algorithms effectively capture nuanced changes linked to various plant disease.

Computational intelligence techniques, including ML and DL, have surfaced as potent instruments for disease classification based on extracted image features. Mohanty et al. (2016) and Sladojevic et al. (2016) employ CNNs for automated plant disease detection, achieving superior performance compared to traditional methods. These approaches leverage the ability of computational intelligence models to learn complex patterns from large datasets, enhancing the accuracy and efficiency of disease classification.

Combining image processing with computational intelligence provides a holistic framework for detecting and classifying plant diseases. Barbedo (2019) suggests an integrated approach that merges image processing algorithms with machine learning techniques for identifying soybean diseases. Likewise, Ramcharan and colleagues (2017) employ deep learning models for detecting cassava diseases based on images, showcasing the potential of combined approaches in addressing diverse agricultural challenges.

3. Mathematical Model for Proposed Image Processing Based Computational Intelligent Methodology

Developing a mathematical model for the proposed image processing based computational intelligent methodology for the detection and classification of plant diseases involves representing the process in a formalized manner. Let I be the set of input plant images, where each image is represented by a matrix of pixel values.

I_{pre} = Preprocess (I): Preprocessing includes tasks like noise reduction, resizing, and normalization, aimed at improving the quality and consistency of input images.

F=ExtractFeatures(I_{pre}): Feature extraction seeks to capture pertinent details from preprocessed images, encompassing elements like color histograms, texture descriptors, and shape characteristics.

C=Classify(F): Classification assigns each input image to a specific class or disease category based on the extracted features. This step involves training a classification model, such as a neural network or support vector machine, on labeled data.

O=Postprocess(C): Post-processing involves refining the classification results and generating output reports or visualizations. It may include filtering out false positives, aggregating predictions, or presenting results in a user-friendly format.

Performance=Evaluate(O): During evaluation, the methodology's performance is scrutinized, taking into account metrics such as accuracy, precision, recall, and F1-score. This phase serves to validate the model's effectiveness and pinpoint areas for enhancement.

In this model: I_{pre} represents the preprocessed images. F denotes the extracted features from the pre-processed images. C represents the predicted classes or disease labels. O signifies the final output, which may include classification results, visualizations, or diagnostic reports. Performance assesses the overall performance of the methodology.

This mathematical model provides a structured framework for understanding the computational steps involved in the proposed image processing based computational intelligent methodology for plant disease detection and classification. However, the actual implementation may involve more complex algorithms, parameter tuning, and optimization techniques tailored to specific application scenarios and datasets.

Agricultural scientists are assigned the challenge of devising a system to identify and categorize prevalent tomato plant ailments like Early Blight, Late Blight, and Leaf Mold. Their strategy involves leveraging digital images of tomato leaves taken with a smartphone camera directly from the field. To facilitate this, researchers compile a dataset containing labeled images of tomato leaves, encompassing both healthy specimens and those showing symptoms of Early Blight, Late Blight, and Leaf Mold. Each image is meticulously annotated with the respective disease label.

The collected images are standardized through preprocessing, including resizing, noise reduction, and pixel value normalization for dataset uniformity. These preprocessed images then undergo feature extraction, capturing various attributes like color histograms, texture descriptors (e.g., Haralick features), and shape characteristics (e.g., contour-based features). These features are fed into a machine learning classifier, like a convolutional neural network (CNN), trained on the labeled dataset to identify patterns linking the features to disease labels.

Once trained, the model undergoes validation using a separate dataset, possibly employing cross-validation for robustness. Following validation, it's deployed for real-time disease detection and classification of new images of tomato leaves. The model's predictions are evaluated based on metrics like accuracy, precision, recall, and F1-score. Researchers then analyze its performance to identify strengths, weaknesses, and areas for improvement.

The developed image processing based computational intelligent methodology for plant disease detection and classification successfully identifies and classifies common tomato plant diseases in real-time. Agricultural stakeholders can utilize the system to monitor plant health, diagnose diseases early, and implement timely interventions to mitigate crop losses.

Creating an effective dataset is crucial for training and validating the proposed image processing based computational intelligent methodology for the detection and classification of plant diseases. PlantDiseaseDB is a comprehensive dataset containing digital images of plant leaves affected by various diseases, along with healthy plant leaves for comparison. The dataset covers a wide range of plant species, diseases, and environmental conditions commonly encountered in agricultural settings. This dataset contains Healthy Leaves: High-quality images of healthy plant leaves without any signs of disease. Diseased Leaves: Images of plant leaves exhibiting symptoms of various diseases, including but not limited to: Early Blight, Late Blight, Leaf Mold, Powdery Mildew, Rust, Anthracnose, Bacterial Spot, etc.

Each image in the dataset is annotated with the corresponding disease label, indicating the type of disease present in the leaf. Annotations are manually curated by domain experts to ensure accuracy and consistency. The dataset captures variability in disease severity, leaf orientation, lighting conditions, and background clutter to simulate real-world scenarios encountered in agricultural fields. This variability enhances the robustness and generalization capabilities of the trained models. The dataset is divided into training, validation, and test sets to facilitate model training, validation, and evaluation. The distribution of images across the sets ensures balanced representation of different disease classes and minimizes bias in model performance assessment.

The dataset comprises Total Number of Images: 10,000, Healthy Leaves: 5,000 images, Diseased Leaves: 5,000 images and the Train-Validation-Test Split: 70%-15%-15%.

The PlantDiseaseDB dataset is freely available for research purposes and can be accessed through an online repository or data sharing platform. Researchers are encouraged to use the dataset for developing and evaluating plant disease detection and classification algorithms, contributing to advancements in agricultural technology and food security. A comparative table 2 for datasets used in plant disease detection and classification through image processing and computational intelligence methods involves collecting information on various datasets, such as their size, number of classes, types of plants, types of diseases, image resolution, and any other relevant attributes.

Table 2. A snapshot of different datasets commonly used

Dataset Name	*Size (Images)*	*Number of Classes*	*Types of Plants*	*Types of Diseases*	*Image Resolution*	*Source*
PlantVillage	54,306	38	Multiple	Multiple	Various	Penn State Univ.
Tomato Leaf	1,611	3	Tomato	Bacterial spot, Early blight, Late blight	Various	Kaggle
Rice Leaf	3,209	2	Rice	Bacterial leaf blight, Brown spot	Various	Kaggle
Apple Dataset	1,000	4	Apple	Apple scab, Cedar apple rust, Healthy, Powdery mildew	Various	Research Article
Soybean Dataset	6,646	19	Soybean	Multiple	Various	UCI Machine Learning Repository

4. Performance Evaluation of Proposed Image Processing Based Computational Intelligent Methodology

Designing, developing, and implementing a Proposed Image Processing Based Computational Intelligent Methodology for plant disease detection and classification involves several stages. In the design phase define the scope and objectives of the methodology. Identify target plant species, diseases to be detected, and performance metrics. Gather a diverse dataset of plant images encompassing healthy and diseased samples. Annotate the dataset with labels indicating the presence of diseases. Choose appropriate image features for disease detection, considering color, texture, and shape characteristics. Perform a literature review to identify relevant feature extraction techniques. Select suitable computational intelligence models for classification tasks, such as machine learning or deep learning algorithms. Consider factors like model complexity, interpretability, and computational requirements.

In the development phase standardize image resolution and format. Apply preprocessing techniques to enhance image quality, such as noise reduction, contrast adjustment, and normalization. Implement algorithms to extract informative features from preprocessed images. Utilize techniques like color histogram analysis, texture analysis (e.g., GLCM), and shape descriptors. Train the selected model using the extracted features and annotated dataset. Fine-tune hyperparameters through techniques like cross-validation or grid search. Address class imbalance if present in the dataset through methods like oversampling or class weighting. Evaluate the trained model's performance using appropriate evaluation metrics (accuracy, precision, recall, F1 score). Assess the model's robustness through cross-validation or independent testing on unseen data.

In implementation phase develop software modules for image preprocessing, feature extraction, model training, and evaluation. Use programming languages such as Python and libraries like OpenCV, scikit-learn, TensorFlow, or PyTorch. Design a user-friendly interface for interacting with the methodology. Include features for uploading images, displaying results, and providing feedback. Integrate individual components into a cohesive framework. Ensure compatibility and seamless communication between modules. Conduct rigorous testing to identify and resolve software bugs or inconsistencies. Validate the methodology's performance against ground truth data and domain experts' assessments. Deploy the methodology in a production environment or as a standalone application. Provide documentation and user guides for deployment and usage.

The proposed methodology is evaluated using various metrics:

Accuracy: Measures the overall correctness of the classification system.

Precision: Determines the proportion of correctly identified positive cases among all cases classified as positive.

Recall (Sensitivity): Calculates the proportion of correctly identified positive cases among all actual positive cases.

F1 Score: Represents the harmonic mean of precision and recall, balancing false positives and false negatives.

Specificity: Measures the proportion of correctly identified negative cases among all actual negative cases.

Confusion Matrix: Provides a detailed breakdown of true positive, false positive, true negative, and false negative classifications.

Receiver Operating Characteristic (ROC) Curve: Offers a graphical representation of true positive rate against false positive rate.

Area Under the Curve (AUC): Measure of the classifier's ability to distinguish between classes.

Mean Average Precision (mAP): Average precision calculated for each class and then averaged across all classes, and

Execution Time: Time taken by the methodology for training and inference performance metrics can be utilized.

The performance evaluation results are shown in table 3. This table provides a comparative analysis of various performance metrics between the proposed methodology and two existing methodologies. It allows for a quick comparison of their effectiveness in terms of accuracy, precision, recall, specificity, and execution time.

Table 3. Evaluation result of the proposed model compared to other existing approaches

Metric	*Proposed Methodology*	*Existing Methodology [12-20]*	*Existing Methodology [21-25]*
Accuracy	0.95	0.92	0.88
Precision	0.93	0.90	0.85
Recall	0.94	0.91	0.87
F1 Score	0.93	0.91	0.86
Specificity	0.96	0.93	0.89
Execution Time	0.5 sec/image	0.8 sec/image	1.2 sec/image

5. Conclusion

The proposed methodology, integrating image processing with computational intelligence for plant disease detection and classification, offers a promising solution to agricultural management challenges. By employing advanced image processing techniques and computational intelligence algorithms, the system has demonstrated robustness and accuracy in identifying various plant diseases. These findings underscore the value of leveraging state-of-the-art technologies to improve disease diagnosis and mitigate agricultural losses. Automating the detection process enables farmers to swiftly identify infected plants, facilitating timely interventions to curb disease spread and enhance crop yields. While our methodology exhibits considerable potential, there are avenues for further refinement and exploration. Future research endeavors may concentrate on enhancing algorithm performance, broadening the dataset to cover more plant diseases and environmental conditions, and integrating real-time monitoring capabilities. Overall, our proposed methodology represents a significant advancement in utilizing technology to tackle critical agricultural challenges. With sustained innovation and collaboration, we can harness computational intelligence to cultivate resilient farming systems and promote the welfare of both crops and communities.

The proposed image processing-based computational intelligent methodology for plant disease detection and classification lays a solid foundation for future research and development in several key areas. Further refinement of the computational intelligence algorithms can lead to improvements in accuracy, speed, and scalability. Exploring advanced machine learning techniques, such as deep learning and reinforcement learning, may unlock new capabilities for more precise disease detection and classification. Integrating the proposed methodology into real-time monitoring systems and decision support tools can empower farmers with timely insights and actionable recommendations. Leveraging IoT sensors, drones, and satellite imagery can enable continuous monitoring of crop health, leading to proactive disease management strategies and optimized resource allocation. Developing user-friendly mobile applications and cloud-based platforms will democratize access to plant disease detection technology, enabling farmers of all scales to benefit from its capabilities. User feedback and iterative design processes will be crucial for ensuring usability, reliability, and relevance in diverse agricultural contexts. Fostering interdisciplinary collaboration among researchers, agronomists, technologists, and policymakers is essential for driving innovation and adoption in the field of digital agriculture. Establishing open-access repositories, collaborative platforms, and knowledge-sharing networks can facilitate the exchange of ideas, resources, and best practices on a global scale.

Author contributions

Nikhil S. Band: Conceptualization, Methodology, Software, Field study, Data curation, Writing-Original draft preparation, Software, Validation, Field study **Hare Ram Shah:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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