Enhancing Plant Disease Detection in Image Processing: A Comprehensive Review

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Abstract:

Plant disease detection is crucial for global food security and sustainable agriculture. Image processing techniques offer non-intrusive and rapid disease identification. However, their efficacy depends on carefully selected hyperparameters, significantly impacting accuracy and efficiency. This review explores the significance and challenges of using hyperparameters in plant disease detection through various classification schemes and methodologies. It addresses computational costs and emphasizes the need for efficient approaches. Hyperparameter tuning enhances system performance, demonstrating the potential of deep learning architectures with specific hyperparameters. This review provides insights for future research, advancing sustainable agriculture and global food security.

Keywords: Plant disease detection, Global food security, Sustainable agriculture, Image processing techniques, Hyperparameters.

1. Introduction:

Since the population of the earth grows by about 1.6% annually, there is a larger demand for plant-based products. To meet the growing demand for food, both in terms of quantity and quality, protecting crops from plant diseases is crucial [1]. Plant illnesses are thought to cost the world economy $220 billion USD per year in monetary terms. According to the Indian Council of Agricultural Sciences, pests and illnesses cause a yearly loss of over 35% of agricultural productivity. In light of this alarming rise in the number of pests and diseases, food security is under jeopardy. The social, ecological, as well as economic activities have all been significantly impacted. For those who engage in agriculture, accurate plant disease identification is still essential [2]. As a result, diagnosing diseases is a very significant step in agriculture. Rice, tomato, potato, and pepper plant cultivation can be negatively impacted by plant diseases and chemical fertilizers, in particular. As a result, to avoid significant losses to crops, a more thorough diagnosis and prompt effective care are required. Finding plant diseases early on is crucial because they can have an adverse effect on both human and animal health and drastically alter agricultural yield in terms of both quantity and quality [3]. Numerous bacterial and viral infections can affect the development, operation, and structural characteristics of commodities and vegetation, which ultimately has an effect on the people that are dependent on them. Due to the difficulty of spotting plant illnesses early on and the detrimental effects on yield, the majority of farmers continue to implement manual methods [4].

If agriculture dominates the nation as a whole and serves as the primary industry and source of revenue, the economy may suffer as a result. Finding and identifying illness in fields at the outset is crucial for preventing crop loss and improving the quality of the crop. According to statistics, 17% of India's GDP comes from agriculture, which is responsible for supporting 70% of the country's people either directly or indirectly. Thirty to three-three percent of all output losses in India are attributable to pest infections. Bacteria, viruses, or fungus may be the source of plant infections [5].

2. A Summary of Processing Images Methods for Detecting Plant Disease:

Fruits and vegetables rank among the major agricultural products. In order to produce more usable items, a product quality check is generally required. Numerous studies have shown that plant diseases can affect the level of quality in agricultural products. Diseases alter or halt vital processes including photosynthesis, transpiration, pollination, fertilization, germination, etc., which harm the plant's ability to function normally. Pathogens such as viruses, fungi, and bacterial agents as well as unfavourable surroundings cause these diseases. In light of this, it is crucial to diagnose plant diseases at an early stage. Experts must always keep an eye on agriculturalists, which could prove very expensive and laborious. Finding a quick, affordable, and reliable way to diagnose illnesses based on symptoms that show up on plant leaves is therefore very important. This makes machine vision possible, which will allow for robot guiding and image-based automatic inspection [6]. In order to help agricultural fields identify plant leaf diseases and appropriately report them to the respective individuals with the appropriate accuracy levels, AI, IoT, along with unmanned aerial vehicles have been combined together. Due to the challenges that farmers face on a daily basis in this modern society, nobody is interested in farming or agriculture. To ensure a safe lifestyle and prevent obstacles like this in agriculture fields, it is imperative that the entire youthful generation relocates to modern cities. A realistic change in the climate and in agriculture is directly associated with the issue of plants' protection from plant diseases [7]. According to studies, the climate change may modify the stages and rates of pathogen growth, as well as the host's resistance, which may influence physiological host-pathogen co-operations [8]. The fact that diseases can now spread more easily than ever before across the world aggravates the situation. New diseases may appear in areas where they have not yet been recognized and, naturally, where there is a scarcity of local expertise to treat them [9].

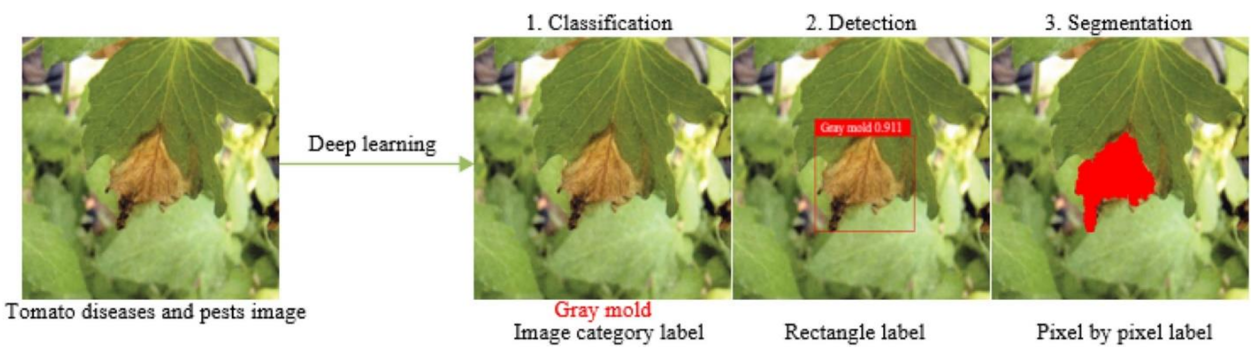

Fig. 1 Plant diseases and pests detection problem [10]

According to Prashar [11], precision agriculture is a smart method of farm management that uses digital technologies, sensors, microcontrollers, actuators, robots, and communication systems to achieve sustainability, financial success, and environmental preservation. In order to maximize farm harvests and promote self-sufficiency in farming operations, Swaminathan [12] characterized it as the integration of various computer technologies into conventional agricultural processes.

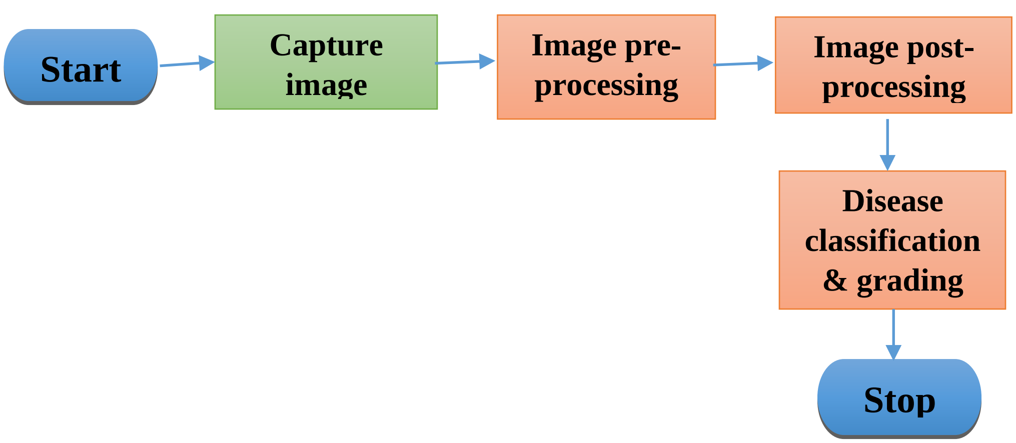

Fig. 2 Flow chart for detection

Khakimov, A. [13] asserts that early diagnosis of the disease's root causes enables prompt decision-making regarding the best kind of protection and guarantees crop protection. There are several traditional methods to recognise diseases of plants, but in the past few years, novel methods and devices for recognizing infectious agents have been created and put to use in an attempt to ensure the quickness and accuracy of diagnoses and do away with the shortcomings of traditional testing. The researchers also discussed cutting-edge approaches to illness diagnosis and pathogen identification that are commonly employed in the modern world, including mass spectrometry, molecular-genetic (and phylogenetic) identification, as well as immunodiagnostics.

3. Hyperparameters in Machine Learning Models:

In country or semiurban settings, where the great majority of Indians live, agriculture is a major income source. The agricultural industry also makes a substantial contribution to the Indian economy. Crop infections have the potential to significantly reduce crop quality and production [14]. Therefore, early disease detection, prevention, and management are extremely important. Several researchers have already proposed several computer vision-based autonomous disease detection methods at this time [15]. Recently, methods for identifying plant diseases using deep learning (DL) have been proposed, including convolution neural network (CNN) and deep belief networks. These methods include training a network to comprehend the underlying features of the images in order to recognize subtle disease symptoms that conventional image processing techniques would be unable to identify. High-resolution images can benefit from using DL models since they can handle complex and huge images [16]. However, a significant amount of labeled training data is required for these strategies, and they might not be suitable for diseases that are not yet known to exist. Another disadvantage of DL models that may be a problem for some applications is their high computational cost. The machine learning algorithms' hyperparameters are notoriously hard to change without a lot of computational effort [17]. The greedy search and swarm intelligence algorithms might be used to provide a practical method for modifying the values of hyperparameters. For achieving this, grid searches and random searches have both shown to be efficient and promising optimisation techniques. Convergence or running time may be slowed down by the expensive objective functions used by these searches and the small population of early answers [18].

4. Literature Review

The main objective of disease detection has consistently been to boost productivity via early diagnosis of illnesses that are affecting the plant. Combining current knowledge with a range of image processing methods and machine learning is beneficial for correctly diagnosing these cotton leaf diseases. methodologies. The proposed DCNN model performed 1000 epochs of training on MGPUs in the environment. The best hyperparameter settings were chosen at random using the coarse-to-fine searching method to enhance the DCNN model's suggested training performance.

Plant diseases are unfavourable factors that drastically reduce crop output and quality. Expert biologists or farmers regularly examine plants with their unaided eyes to look for disease, despite the fact that this approach is frequently incorrect and can take a lot of time.

According to **Jung, et al. (2023) [21]**, early detection of crop disease is substantial for crop quality and productivity since it allows for the selection of the most effective treatments. However, specializing in plant pathology and having years of experience are necessary for disease identification. To create automated system, a CNN method with five pre-trained models was used in conjunction with images of diseased and healthy plant pairings to design a stepwise disease detection model. The three components of the disease detection model are crop categorization, disease detection, and sickness classification. The "unknown" is included in the categories to make the model more universally applicable. The disease identification algorithm accurately (97.09%) identified the types of crops and diseases throughout the validation test. The inclusion of these crops in the training dataset increased the low accuracy of non-model crops, indicating that the model is not necessary. Once more different crops are included in the training dataset, our model will be extensively used and may even be applied to smart farming of Solanaceae crops.

Plant diseases cause devastating food loss, as farmers struggle to supply the world's rapidly expanding population with enough agricultural products. Agriculture industry spending on disease prevention amounts to billions of dollars, yet without any scientific assistance, disease control is frequently ineffective. Advances in computer vision techniques help in the early identification of plant illnesses with the use of an adaptable algorithm constructed utilising machine learning and deep learning technologies. In their research to enhance the hyper parameters of the DenseNet-121 architecture.

For several decades, tomato plant diseases brought on by microorganisms like fungi, bacteria, and others have threatened the quality and output of tomatoes, according to **Y. Y. Chua et al. (2022) [23]**. Therefore, it is important to take precautions in the early stages to find and treat illnesses that have already shown on plant leaves before they spread and kill the plant. However, the current detection method is unpredictable and inefficient. The majority of farmers utilise manual visualisations to detect the various plant ailments since automatic disease monitoring and classification is not feasible. To solve these challenges, an artificial intelligence (AI)-based detection of plant diseases system must be developed. Given that it had a 100% accuracy rate and needed less training time overall, the ResNet-50 model was suggested as the best one to use in the system for categorising for tomato plant diseases. Tomato producers are anxiously expecting the advantages of a CNN model that has been created.

5. Challenges in Hyperparameter Selection for Plant Disease Detection:

Agriculture is severely harmed by plant diseases, which reduce yields significantly. Deep learning techniques have lately gained in popularity, and as a result, powerful tools that yield incredibly accurate results in the identification of plant diseases have been developed. The shortcomings and deficiencies of the models currently in use to diagnose plant diseases are presented and discussed by Arsenovic et al. (2019) [24]. In addition, to break the previous record for the biggest dataset of leaf photos, a brand-new dataset including 79,265 images was given. Images were taken under a range of weather situations, from various angles, and with a background that resembled actual scenarios. Both traditional augmentation methods and cutting-edge generative adversarial networks were used to expand the number of photos in the collection. Several tests were done to see how well training in a safe setting would work and how well it would work in actual situations, including detecting numerous diseases in a single leaf or reliably identifying plant diseases in a background with a lot of different elements. Finally, for the purpose of classifying plant diseases in a real setting, a novel two-stage neural network design was presented. Accuracy was 93.67% for the trained model. Using photographs of the entire affected plant, including the leaf, fruit, root, etc., **Restrepo-Arias et al. (2022) [25]** has proposed a brand-new approach to disease diagnosis. Their study provides a strategy to mitigate the categorization bias caused by leaf morphology. The extraction of textural components forms the basis of this technique. In addition, Bayesian optimization is advised in order to get training hyperparameters that enhance artificial neural network training. The PlantVillage dataset's images were first pre-processed by the researchers to remove background noise. To remove any potential bias from leaf form, tiles from images were utilised later. Finally, a number of advanced, small convolutional neural networks (CNNs) were trained on a fresh dataset of 85 x 85 x 3 px images. These CNNs were designed for situations with limited processing resources. The models that predicted the best outcomes were MobileNet and SqueezeNet, both of which had accuracy rates of 96.31% and 95.05%, respectively. The agri-food business can make decisions more easily thanks to these intelligent approaches' systems and processes. The automatic identification of plant diseases has been one of the application areas, according to **Marco-Detchart C et al. (2023) [26]**. With the help of these techniques, which are mostly based on deep learning models, it is feasible to analyze and categorize plants in order to identify potential diseases, facilitating early diagnosis and so preventing the disease's spread. Their research proposes an Edge-AI system with the necessary hardware and software components for autonomously identifying plant illnesses from an assortment of photographs of a plant leaf using the aforementioned method. Numerous studies have demonstrated that using this device considerably accelerates the resistance of categorization reactions to alleged plant diseases.

6. Case Studies and Comparative Analysis:

On 2.5% of the land used for agriculture, cotton is produced as an industrial crop in monoculture to produce natural fiber. Cotton is a drought-resistant crop that offers farmers in climate change-vulnerable areas a steady source of income. The low yield of these cotton crops is attributed, in part, to the fungal, viral, bacterial, and other parasite diseases that may fluctuate as a result of climatic circumstances, according to Sandeep Kumar et al. (2021) [27]. The leaf is the part of the plant most vulnerable to illnesses, which can harm the plant as a whole and occasionally the entire crop. The majority of illnesses only affect cotton plant sections that have leaves. The fundamental goal of disease detection has always been to use conventional methods to detect diseases early on in the plant's life cycle to improve productivity. In order to appropriately diagnose these cotton leaf diseases, a combination of existing knowledge, various image processing techniques, and machine learning methodologies are helpful.

The automatic leaf disease diagnostic system relies largely and critically on the feature extraction technique. According to **Sapkal et al. (2018) [28]**, numerous feature extraction approaches, such as color, shape, texture, HOG, SURF, and SIFT features, are employed by researchers to diagnose leaf diseases. Recent developments in computer vision show great promise for deep learning. They analyze and contrast two feature extraction methods in their study. For the first method, the Gray Level Covariance Matrix (GLCM), which extracts 12 texture properties for diagnostic purposes, is utilized. In the second method, Alexnet's pretrained deep learning model is utilized for feature extraction. This pretrained model assists in the automatic extraction of 1000 characteristics. In this case, classification is accomplished using a backpropagation neural network (BPNN). The deep learning characteristics are seen to be more prevalent than the texture features. Compared to the texture feature extraction method utilized here, it provides accuracy of 93.85%.

Pest infections and bacterial or viral contagions cause financial losses for the crop agriculture sector. Nearly 10–20% of the nation's annual profit is lost by farmers in India. By using deep learning techniques to assess the crop's status, **Singh, A., et al.'s (2020) [29]** solution to the aforementioned agricultural issue was put out. Our system analyzes features from leaf images, identifies the features as diseases, and generates diagnostic to stop the spread of disease by performing the necessary damage control measures. The researchers have used a dataset of 14 crops and their 26 underlying diseases to help train the model for accurate disease detection. The trained models employing Deep Convolutional Neural Networks, Residual Networks and Recurrent Convolutional Neural Networks provide a performance reaching a 99% success rate in determining the corresponding crop diseases. Our system also provides relative precautionary information from a sourced database to tackle the diseases that are recognized by the classifier. The application of this system is a useful advisory warning tool for the farmers, agricultural workers and agronomists for the identification of diseases in the early stage so that immediate action can be taken. Large-scale crop losses could be reduced as a result, assisting the agricultural sector and reducing associated economic damage.

Modern deep learning (DL) architectures have recently been used to classify plant diseases from datasets that have been created by authors or made publically available. In two steps, **Saleem MH et al.'s** research from **2020 [30]** suggested classifying plant diseases using deep learning-based comparative evaluation. **Future Directions:**

Looking ahead in plant disease detection and image processing, the Hyperparameters Classification Scheme for Detecting Plant Diseases looks promising for future advancements. To improve performance and generalizability, diverse datasets should be explored. Investigating novel deep learning architectures and algorithmic improvements can lead to substantial gains. Integrating multi-sensor data can enhance disease detection, while optimizing computational efficiency enables on-site, real-time detection. Exploring interpretability techniques builds trust, and collaborations among researchers, practitioners, and stakeholders ensure practical alignment. Field testing is crucial for validation and identifying potential limitations. Overall, embracing these opportunities can revolutionize plant disease detection, advancing sustainable agriculture and food security.

7. Conclusion:

Image processing techniques have proven to be invaluable tools for non-intrusive and rapid disease identification. However, the optimal performance of these methods hinges on the thoughtful selection of hyperparameters, which profoundly impact accuracy and efficiency. Through a comprehensive exploration of various classification schemes and methodologies, this review sheds light on the significance and challenges of hyperparameter utilization in plant disease detection. By addressing computational costs and advocating for efficient approaches, it underscores the need for scalable solutions applicable in real-world scenarios. The demonstrated effectiveness of hyperparameter tuning in enhancing system performance, particularly in deep learning architectures, further underscores the potential for accurate disease classification. These insights provide a valuable roadmap for future research and development, propelling advances in sustainable agriculture and securing global food supplies for generations to come.

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