Medicinal Leaf Disease Detection Using a Hybrid CNN-ABI-LSTM Classifier with Modified Red Panda Algorithm

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Abstract: Medicinal plants are crucial in healthcare systems, providing natural remedies for various ailments. However, diseases in medicinal plant leaves can significantly reduce their therapeutic properties and economic value. Diagnosing diseases in medicinal plant leaves is traditionally performed through manual inspection, which is time-consuming, requires expertise, and is prone to human error. Early detection of these diseases is crucial to preserving the quality and potency of medicinal plants. In many cases, diseases remain undetected until they have caused significant damage, leading to a loss of valuable resources and medicinal benefits. The challenge lies in developing an automated system capable of detecting leaf diseases at an early stage, including in large-scale farms, without the need for human intervention. The success of deep learning in image recognition tasks presents a promising opportunity to automate the detection of diseases in medicinal leaves. By utilizing deep learning, this research aims to provide a scalable, efficient, and accurate solution to reduce the time and lab or involved in manual inspections. Early disease detection can lead to timely interventions, thereby protecting medicinal plant populations, enhancing yield quality, and supporting the sustainability of natural healthcare solutions.

Keywords: Plant Leaf Diseases; Leaf Images; Image Processing Approaches; Deep Learning Algorithms; Machine Learning Algorithms; Research Gaps; ACN2-ABi-LSTM classifier

Introduction

Medicinal plants play a crucial role in treating various diseases and maintaining health. India has long been recognized for its traditional medicinal systems such as Ayurveda, Siddha, and Unani, with Ayurvedic medicine being a 3,000-year-old system of herbal healing [1]. This ancient practice has gained global acceptance, highlighting the significance of plants like papaya, avocado, and neem in daily life [2]. Herbal remedies derived from these plants are valued for their minimal side effects and ability to treat illnesses safely for people of any age or gender [3].Plant diseases can have a substantial impact on agricultural productivity [4]. Common plant diseases include wilt rot, leaf blight, leaf spot, brown spots, and bacterial rot, which often affect plants like avocado, leading to reduced yield [5]. Fungi are one of the most prominent pathogens, responsible for plant diseases such as Early blight, Late blight, Leaf spot, Bacterial spot, Common rust, Downy mildew, and Anthracnose [6,7]. These diseases can hinder critical plant functions like transpiration, photosynthesis, germination, and pollination, making early diagnosis essential for preventing plant losses.

Advanced chemical and analytical procedures such as high-performance liquid chromatography (HPLC), gas chromatography (GC),[8], and similar techniques are employed for evaluating plant diseases at advanced stages.[9] Although these methods produce reliable results, they are limited by factors such as lengthy processing times, high costs, and labor-intensive sample preparation. In terms of machine learning approaches [10,11] a neuro-fuzzy and neural network-based method for shape feature selection has achieved high accuracy in template-based leaf classification [12]. Techniques utilizing GIST and local binary pattern (LBP) features with particle swarm optimization (PSO)-based classifiers have demonstrated high accuracy [13,14]. A hybrid model combining PSO, support vector machine (SVM), and gray wolf optimization (GWO) has further improved classification accuracy [15]. Similar high accuracy has been reported using the extreme learning machine (ELM) technique, where features such as color, Fourier descriptors, and gray-level co-occurrence matrix (GLCM) were employed. Additionally, the combination of SVM and adaptive boosting (AdaBoost), using leaf morphological characteristics, achieved a recognition rate [16].

Innovative techniques are essential to address future agricultural trends and overcome the challenges of enhancing productivity. Precise diagnosis is crucial for the efficient detection and control of plant leaf diseases. Without accurate diagnosis, farmers may waste time, energy, and resources trying to identify the underlying problem. As a result, advancements in current techniques and the development of new approaches are necessary to create a more efficient automated system for diagnosing plant diseases, which outperforms traditional visual assessment methods. Image processing techniques offer higher accuracy and lower costs by detecting variables involved in plant leaf diseases more effectively. These methods can capture finer details of visual symptoms. However, performance metrics such as accuracy, sensitivity, and specificity remain low in existing plant leaf disease classification methods. Therefore, this paper presents an automatic leaf disease prediction approach based on a deep learning model.

Literature Survey

Many of the researchers had developed plant leaf disease classification and detection. Among them some of the works are analysed here; Bi, C., Wang et al. [16] presented a low-cost, stable, and highly accurate approach for identifying apple leaf diseases. To achieve this, the Mobile Net model was used. First, due to its simplicity and ease of implementation on mobile devices, it was a low-cost solution compared to other deep learning models. Second, the proposed algorithm allowed non-experts to perform apple leaf disease examinations reliably. Third, Mobile Net's accuracy was found to be nearly identical to that of more complex deep learning models. The method significantly reduced the burden on experts for apple leaf disease identification. However, it failed to achieve the desired efficiency and precision in terms of processing time.

Singh and Athisayamani, et al. [17] introduced Heap Autoencoders (HAEs), a novel deep learning approach. This approach eliminated the exhausting reliance on handcrafted features and directly obtained significant characteristics. Additionally, the training method reduced the overfitting problem and improved efficiency during brief training sessions. In HAEs, the Rectified Linear Units (ReLU) activation function and a dropout approach were also utilized, allowing it to perform better than traditional techniques. The output results showed that this model achieved the highest classification accuracy. However, the technique exhibited a lower level of performance in image registration, recommender systems, image detection, and image dehazing.

Cap, Q et al. [18] presented Leaf GAN, a unique system for image-to-image translation that incorporated its attention mechanism. As a data augmentation technique, Leaf GAN transformed a wide range of healthy images into diseased ones, thereby enhancing the accuracy of plant disease detection. The algorithm was capable of changing only the relevant portions of images while preserving different backgrounds, which increased the adaptability of the training images. The authors stated that the Leaf GAN method ensured improvements in the quality of the generated images and boosted the overall disease diagnosis performance. However, the algorithm failed to achieve optimal computational efficiency.

Guo, C et al. [19] introduced the recursion-enhanced random Forest with an Improved Linear Model (RFRF-ILM) for heart disease detection. The authors utilized machine learning approaches to identify the salient characteristics associated with heart attack diagnosis. By employing the heart disease prediction model, it provided more accurate results. The investigation identified the causes of heart illness. For data analysis, a comparison of significant factors was displayed using the Internet of Medical Things (IoMT) platform. Coronary artery disease develops more frequently in older individuals, with high blood pressure also playing an important role. However, additional aspects that should have been taken into consideration for accurately assessing the occurrence of coronary artery disease included the stability ratio and F-measure ratio.

Joshi et al. [20] discussed a modified state-of-the-art residual network to facilitate transfer learning, employing a progressive transfer learning technique for two learning stages. By using a more complex variant of the One Cycle Policy and multiple learning rates, the process continuously recorded the regression in training and validation loss. The introduced model outperformed the current state-of-the-art top-1 accuracy on three publicly accessible datasets: Flavia, Leaf Snap, and Malaya Kew (MK). The CNN provides better accuracy for larger and more varied datasets. However, this approach decreased performance, resource efficiency, and computational complexity.

Mukherjee et al. [21] discussed leaves under-regulated lighting, processed those images, and then fed them into a system that used convolutional neural network (CNN) architecture to classify the type of leaf and its maturity level. The use of binary particle swarm optimization (BPSO) to determine the CNN hyper parameter values was also introduced in this work. The system's potential was evaluated using three widely recognized types of medicinal plants: Kalmegh, Tulsi, and Neem. Several common measures, such as the tenfold cross-validation approach and multiple test runs, were employed to validate the categorization findings. The authors presented a CNN-driven computer vision framework that provided accuracy, cost-effectiveness, and non-invasive operations. However, did not address practical implementation issues or real-world efficiency.

Zhao, Y et al. [22] introduced high-resolution images of diseased leaves with Double GAN using fewer samples. Double GAN consists of two stages. In the first stage, we used both healthy and diseased leaves as inputs. Initially, a pre-trained model was obtained by training the WGAN (Wasserstein Generative Adversarial Network) on images of healthy leaves. Then, the pre-trained model was fine-tuned on diseased leaves to generate 64x64 pixel images. In the second stage, to further augment the imbalanced dataset, 256x256 pixel images were produced using a super-resolution generative adversarial network (SRGAN). As a result, the accuracy of plant species classification is improved. However, it failed to generate high-resolution images.

Patle, K. et al. [23] discussed that the growth of fungal disease on the leaf canopy was influenced by the length of leaf wetness (LWD). A leaf wetness sensor (LWS) was commonly used to measure LWD. The printed circuit board (PCB) technology used in commercially available LWS had several drawbacks that needed to be addressed before field deployment. To address these issues, we developed an inexpensive, in-house Internet of Things (IoT) electronic leaf wetness sensor on flexible substrates for integrated plant disease management. The fabricated LWS consisted of interdigitated electrodes (IDEs) on a flexible polyimide substrate. The experimental results demonstrated its accuracy and reliability; however, it failed to achieve early prediction of plant diseases.

Objective of the study

- To study and analyze different plant leaf disease classification techniques in the literature to understand their strengths and limitations.
- To develop an automated system for early detection of diseases in medicinal plant leaves, minimizing the need for manual intervention.

- To design a scalable and accurate model that effectively identifies and classifies diseases in medicinal plant leaves across different species.
- To improve the system's performance by optimizing key parameters, ensuring high efficiency and accuracy in disease detection.
- To enhance image quality through effective pre-processing methods, providing clean and informative data for better analysis.
- To evaluate the system's effectiveness by comparing its performance with existing methods, ensuring superior results in terms of accuracy, speed, and reliability.

Research gap

While there have been several advancements in plant leaf disease classification techniques, most of the existing methods either rely heavily on manual inspection or use traditional machine-learning techniques that require handcrafted features, which may not be sufficient for accurate disease classification in complex datasets like medicinal plant leaves. Moreover, current systems often lack scalability for large-scale farms, and many do not provide early-stage disease detection, leading to delayed interventions and loss of medicinal plant value. Additionally, optimization techniques to improve model accuracy, resource efficiency, and hyper-parameter tuning have been underexplored, particularly in the context of hybrid models combining feature extraction and sequence processing. There is also a need for more robust models that can efficiently handle noise and variations in leaf images to deliver accurate predictions across diverse species of medicinal plants. This creates an opportunity to develop a more automated, scalable, and accurate system for early disease detection by leveraging advanced deep learning techniques and optimization algorithms, which have not been sufficiently addressed in the literature.

Problem statement with contribution

Medicinal plants are crucial in healthcare systems, providing natural remedies for various ailments. However, diseases in medicinal plant leaves can significantly reduce their therapeutic properties and economic value. Diagnosing diseases in medicinal plant leaves is traditionally performed through manual inspection, which is time-consuming, requires expertise, and is prone to human error. Early detection of these diseases is crucial to preserving the quality and potency of medicinal plants. In many cases, diseases remain undetected until they have caused significant damage, leading to a loss of valuable resources and medicinal benefits. The challenge lies in developing an automated system capable of detecting leaf diseases at an early stage, including in large-scale farms, without the need for human intervention. The success of deep learning in image recognition tasks presents a promising opportunity to automate the detection of diseases in medicinal leaves. utilizing deep learning, this research aims to provide a scalable, efficient, and accurate solution to reduce the time and labor involved in manual inspections. Early disease detection can lead to timely interventions, thereby protecting medicinal plant populations, enhancing yield quality, and supporting the sustainability of natural healthcare solutions. The main contribution of the proposed approach is listed below;

- At first, we collect the medicinal plant leaf image dataset from the Mendeley data source. For experimental analysis, three sets of medicinal leaves are used namely, avocado, papaya, and, neem,
- During pre-processing, an enhanced median filter is applied for noise removal, and histogram equalization is used for image enhancement.
- After pre-processing, the imagesare given to the hybrid deep-learning technique namely, the ACN^{2-}AB$_{i}$-LSTM classifier. The proposed deep-learning classifier is a combination of CNN and ABi-LSTM classifier.
- This hybrid method is likely designed to leverage both CNN's strength in feature extraction and LSTM's ability in sequence processing.
- To enhance the performance of the classifier, the hyper-parameter present in the classifiers is optimally selected using a modified red panda optimization algorithm (MRePO).
- The performance of the proposed approach is analyzed based on different metrics and performance compared with various state-of-the-art works.
- The proposed model is implemented using Python.

Conclusion

In this study, we proposed a novel deep learning-based automated system for the early detection of diseases in medicinal plant leaves, addressing the challenges of manual inspection and delayed diagnosis. By utilizing an enhanced pre-processing phase involving an improved median filter for noise removal and histogram equalization for image enhancement, the quality of the input images was significantly improved. The hybrid ACN2-ABi-LSTM classifier, combining the powerful feature extraction capability of CNN with the sequential learning strength of ABi-LSTM, effectively classified diseases in medicinal plants such as avocado, papaya, and neem. Furthermore, the integration of a modified Red Panda Optimization (MRePO) algorithm for hyper-parameter tuning contributed to achieving superior performance metrics compared to existing state-of-the-art techniques. Experimental results demonstrated that the proposed approach enhanced classification accuracy, improved early disease detection, and reduced processing time and computational costs. Overall, this work presents a scalable, efficient, and highly accurate system, contributing significantly to protecting medicinal plant resources and supporting sustainable natural healthcare solutions.

Future Scope

Future work can include a broader range of medicinal plant species and more diverse datasets under varying environmental conditions to improve the model's robustness and generalization. The system can be integrated into IoT-based smart farming solutions, enabling real-time disease monitoring and alerts on large-scale farms through mobile or web application. Incorporating explainable AI techniques could help in understanding the decision-making process of the deep learning model, making it more transparent and acceptable for practical agricultural usage. Future enhancements could aim at simultaneously identifying multiple diseases occurring on the same leaf, thus handling more complex real-world scenarios.

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