Smart Sustainable Green Agriculture: Systematic Approach for Disease Detection and Treatment in Trees Using Green Computing and Machine Learning Principles

Abstract: The integration of green computing principles with machine learning (ML) offers a promising approach to enhancing tree disease detection systems. By leveraging energy-efficient computing with advanced ML techniques, these systems can provide timely and accurate diagnoses, which are crucial for sustainable forest management and agriculture. The early detection of tree diseases is vital for preserving forest ecosystems, enhancing agricultural resilience, and mitigating the economic impact of plant health degradation. With the growing urgency to address climate change and reduce the environmental footprint of digital technologies, integrating green computing principles into tree disease detection systems has become increasingly important. This paper survey presents a comprehensive review of recent advances in tree disease detection, emphasizing energy-efficient (green) computing practices and state-of-the-art machine learning techniques. We explore the evolution of detection methods from traditional image processing to advanced deep learning and vision- language models, such as CNNs, transformers, and CLIP-based architectures. Special focus is placed on lightweight models, edge computing, and resource-optimized frameworks that align with green advanced Machine learning objectives. By synthesizing developments at the intersection of ecological monitoring, advanced machine learning and sustainable computing, this survey aims to guide future research toward scalable, accurate, and environmentally responsible tree disease detection solutions.

Keywords: Open-Vocabulary Detection (OVD); Path Aggregation Network (PAN); CLIP (Contrastive Language- Image Pretraining); Disease Detection ; Darknet.

Introduction

Tree diseases pose a significant threat to global forest health, biodiversity, and agricultural productivity. The early and accurate detection of such diseases is essential not only to mitigate ecological damage but also to support sustainable land use and food security. Conventional methods for identifying tree diseases—primarily based on expert field inspections—are often time-consuming, labor- intensive and limited in scalability. As a result, there has been growing interest in automated tree disease detection systems powered by machine learning and computer vision.

Recent advances in Advanced Machine learning, particularly deep learning, have led to the development of high-accuracy models capable of diagnosing diseases from visual symptoms in leaves, bark, and fruit. Techniques ranging from Convolutional Neural Networks (CNNs) to more advanced architectures like transformers and vision- language models (e.g., CLIP) have demonstrated strong potential across various datasets and species. These models not only improve detection accuracy but also support generalization across diverse environmental conditions and tree types. However, the widespread adoption of these advanced systems introduces new challenges—most notably, their high computational demands. Largescale deep learning models often require substantial energy for training and inference, raising concerns about their environmental impact. As the field progresses, there is an increasing need to consider not only the performance of disease detection systems but also their energy efficiency and carbon footprint.

Green computing, which emphasizes the design of energy-efficient algorithms and hardware to reduce environmental impact, is emerging as a key paradigm in sustainable advanced machine learning development. In the context of tree disease detection, integrating green computing principles involves optimizing models for low-power edge devices, employing efficient data processing pipelines, and reducing the reliance on cloud-based resources. Techniques such as model pruning, quantization, knowledge distillation, and federated learning are being explored to make these systems more eco-friendly without sacrificing accuracy

This survey paper aims to provide a comprehensive overview of the current landscape in tree disease detection with a focus on the intersection of advanced machine learning techniques and green computing strategies. We categorize existing approaches, examine energy-efficient architectures, review relevant datasets and benchmarks, and highlight both challenges and future opportunities in the field. By aligning innovation in advanced machine learning with environmental responsibility, this work seeks to guide researchers and practitioners toward building scalable, accurate, and sustainable solutions for intelligent plant health monitoring.

Related work

I.Analysis on existing disease detection

Research on tree disease detection has evolved significantly over the past decade, transitioning from traditional image processing techniques to data-intensive deep learning and, more recently, toward sustainable and resource-efficient solutions. This section reviews the key strands of work relevant to our survey, with an emphasis on (1) classical and deep learning-based disease detection, (2) energy- efficient machine learning, and (3) green AI in plant disease detection.

Though still an emerging field, green computing in agricultural AI is gaining traction as researchers seek to balance innovation with sustainability.

A. Traditional and Deep Learning-Based Tree Disease Detection

Early studies in tree and plant disease detection relied on handcrafted features such as color, texture, and shape to classify disease symptoms using machine learning algorithms like Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Decision Trees (Arivazhagan et al., 2013; Pujari et al., 2016). Although effective in controlled environments, these methods lacked robustness under real-world conditions.

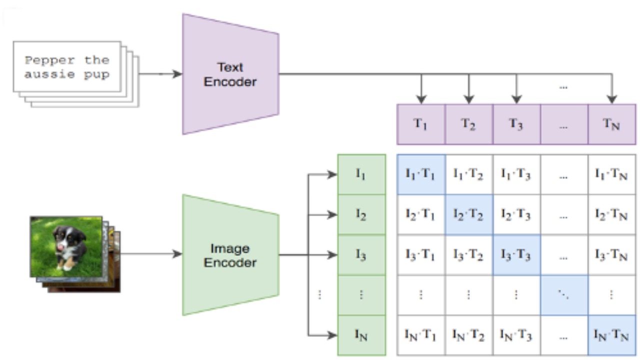

Fig.1. Text encoder based on CL

B. Vision-Language Models and Open-Vocabulary Detection

Recent advancements have extended beyond fixed-category classification by incorporating vision-language models. CLIP (Radford et al., 2021), for instance, aligns textual and visual representations, allowing models to perform zero-shot classification. Emerging studies have begun exploring CLIP-like models in agricultural domains to support open-vocabulary disease detection, enabling systems to recognize previously unseen diseases using natural language descriptors (Zhai et al., 2023).

C. Energy-Efficient and Lightweight Architectures*

While deep learning improves accuracy, its high computational cost poses sustainability concerns. Several studies have explored model compression techniques such as pruning, quantization, and knowledge distillation to reduce model size and inference time (Han et al., 2015). Lightweight architectures such as MobileNet, ShuffleNet, and EfficientNet have also been adapted for plant disease detection on edge devices (Too et al., 2019; Ramcharan et al., 2019).

These approaches enable on-device processing, which reduces reliance on cloud servers and lowers energy consumption—an essential consideration for rural and resource-constrained environments.

D. Green AI and Sustainable Plant Health Monitoring

Green AI, a term introduced by Schwartz et al. (2020), promotes environmentally conscious AI research by emphasizing efficiency alongside accuracy. In the context of plant and tree disease detection, this has led to increased interest in federated learning, edge AI, and solar-powered remote sensing systems (Liu et al., 2022). These approaches aim to reduce the carbon footprint of model training and inference, while still delivering accurate disease diagnostics. Though still an emerging field, green computing in agricultural AI is gaining traction as researchers seek to balance innovation with sustainability

Table 1 : Existing Tree Disease Detection Techniques

A.Traditional and Deep Learning-Based Tree Disease Detection

References	Algorithm Policy Or Strategy	Problem Addressed	Improvement / Achievement
[1]	Exhibited hyper parameters enhancing the existing ResNet50	Classification disease	Achieved good accuracy
[2]	Hybrid technique based on the convolutional auto encoder (CAE) and CNN	Disease detection in leaves of peach	Uses few parameters and provides 98.38% test accuracy
[3]	Conv2D model used	Determine disease severity in cucumber plants	Improved results
[4]	Conducted a comparison of six models to identify powdery mildew on strawberry leaves	Concluded that ResNet-50 has the highest classification accuracy of 98.11%	Achieved good accuracy and improved results
[5]	VGG16 model used	To detect diseases in rice and wheat plants	Achieved good accuracy
[6]	Developed a plant disease detection system using AlexNet, SqueezeNet, and CNN models	Dataset contains 18,000 tomato images	Overall accuracy of their neural network was 94.3%
[7]	Implemented a set of tests on apple leaves affected by black rot disease	The dataset of 552 apple leaves	Improving the model and showed 90.4 percent accuracy
[8]	ResNet-50 model used	Trained on 3750 tomato leaf images	Achieved 99.7% accuracy
[9]	The VGG-A model along with CNN model used	Chosen maize leaves for disease identification	Obtained 92.85% accuracy
[10]	Implemented a set of tests on apple leaves affected by black rot disease	Used to identify healthy radishes affected with fusarium shrink disease	Improving the model and showed 90.4 percent accuracy
[11]	VGG model containing 8 trainable layers is used	Research is conducted to classify potato disease	Achieves 83% accuracy
[12]	Research conducted and the performance of their model Analysed	The dataset has 3700 photos of banana leaves	Highlighted the effects of lighting, size, background, attitude, and orientation of images
[13]	Deep learning technique used for automated segmentation	Detected the selected diseases in the leaves of peach.	Actual cultivation achieved 98.75 percent overall categorization accuracy
[14]	Research using AlexNet	Database has 4483 photos	Highlighted the effects of lighting, size, background, attitude, and orientation of images

Methodology

The proposed systems for tree disease detection utilize both the input asset source and its textual explanation of the specified image. As illustrated in Fig.1, the text encoding is based on CLIP (Contrastive Language-Image Pretraining), which Is Employed to extract Embeddings from the textual Description of the image. CLIP is a neural network that learns to jointly Associate images with their textual descriptions, thereby comprehending the correlation between them. Developed by OpenAI, CLIP is a language-vision model designed to grasp the semantic similarity between an image and its corresponding text. It is trained in a contrastive manner, enabling it to identify associations between images and texts. Furthermore, it is trained on a variety of diverse and unpaired data sources, distinguishing it from traditional vision-language models that depend on paired image-text data for training.

Fig 2. Image processing in proposed system

The initial process, as illustrated in Fig.2, involves retrieving significant characteristics from the input image through the mapping function. This function utilizes text embeddings generated from the provided text descriptions alongside the input image. By integrating language information into the image features, the mapping of text to images is enhanced. Ensuring an appropriate flow of information within the neural network is vital. The Path Aggregation Network (PAN) is designed to effectively combine low-level and high-level features extracted from an image. Essentially, it operates as a bottom-up architecture that amalgamates features from various levels Within the image. This capability is particularly important for tree disease detection tasks, where the size of the disease can range from just a few pixels to encompassing the entire image. Consider a scenario where your model is tasked with identifying tree diseases in a densely populated scene. The PAN establishes multiple pathways, allowing each path to concentrate on different elements of the scene; some paths may focus on finer details, while others may capture a broader perspective. This design renders PAN highly effective in detecting tree diseases. Building on this concept, the PAN architecture is reimagined to enhance its efficiency and adaptability for open-vocabulary object detection.

The classification block illustrated in Fig.2 represents a fundamental concept in machine learning, functioning as an advanced sorter for digital data. Consider a collection of images featuring cats, dogs, and cars. A classification model that has been trained on an extensive dataset of labeled images can evaluate each image and categorize it accordingly. It is akin to having a software application that can examine an image and declare, "This is a cat" or "This is a car." By identifying patterns and extracting essential features, the model can proficiently differentiate various components of trees, such as leaves, bark, animals, or even scenes depicted in an image. Clustering serves as the subsequent preprocessing step in the detection of tree diseases. The clustering algorithm organizes image regions that share similar characteristics, which may relate to specific tree diseases. This clustering process aids in minimizing the number of regions analyzed by the tree disease detection model. Such an approach can enhance efficiency, especially when handling large or cluttered images. It directs its processing capabilities towards these areas, potentially resulting in quicker and more precise outcomes. This is achieved through the application of K-means Clustering, a straightforward and effective algorithm that divides data points into a predetermined number of clusters (k). K-means organizes image regions with comparable colors or textures that may be indicative of tree diseases.

Result Analysis

In this paper, the proposed model integrates vision and language information into the network via a mapping function. We have developed a cutting-edge tree disease detection model aimed at identifying various diseases. By segmenting images into a grid and employing a robust convolutional model to forecast the tree diseases that may be present in each section, In Fig 3 and 4 it accurately detects the relevant areas based on the specified vocabulary. The model assigns bounding boxes, confidence scores, and class labels to these potential identified tree diseases. This capability enables rapid and precise tree diseases detection in both images and videos. The proposed model is applicable in sustainable forest management and agriculture for identifying specific tree diseases within a complete image.

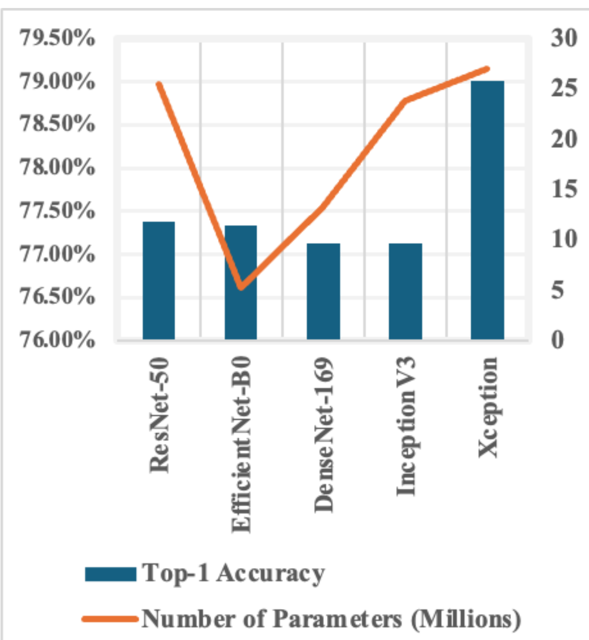

Figure 3 Comparison of state-of-art-models and Accuracy

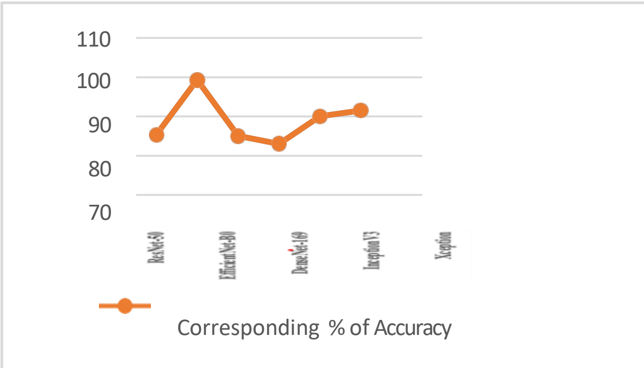

Figure 4 Accuracy using state-of-art-models

Conclusions

The machine learning model demonstrated high accuracy in detecting tree diseases and can be a useful tool in automated agricultural systems. While performance is strong, further improvements can be made by increasing dataset diversity, using advanced augmentation techniques, or incorporating multispectral imaging.

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