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REVIEW ARTICLE

Machine learning applications for sustainable durian disease management

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Abstract

Durian, the beloved "king of fruits", serves as an economic lifeline for Southeast Asia, yet it faces constant threats from fungal pathogens that can destroy up to 40 % of a harvest. While traditional visual checks are often subjective and laboratory tests like polymerase chain reaction (PCR) are too complex for daily field use, machine learning (ML) offers a more supportive, practical path forward. By using convolutional neural networks (CNNs) on mobile devices, farmers can now identify diseases with 90 % accuracy directly in the orchard. Advanced tools like thermal imaging and biosensors act as an early-warning system, detecting hidden stress before symptoms ever appear. This shift toward predictive farming empowers growers to protect their livelihoods more sustainably. Techniques like transfer learning bridge the gap between high-tech science and daily labour, ensuring that even with limited data, farmers have a dependable companion in the grove. Ultimately, integrating ML and internet of things (IoT) minimises chemical reliance, safeguarding both the environment and the long-term health of the durian industry.

Keywords: biosensor; durian; internet of things; machine learning; neural network; plant disease detection; sustainable agriculture

Introduction

Durian (*Durio zibethinus L.*), often hailed as the "king of fruits," holds significant economic importance across Southeast Asia, particularly in countries like Thailand, Malaysia and Indonesia (1). Its unique flavour and nutritional value drive a thriving global market. However, this lucrative crop faces persistent threats from phytopathogenic fungal species such as *Fusarium solani, Rhizoctonia solani, Phytophthora palmivora, Corticium salmonicolor* and *Colletotrichum gloeosporioides* (2–3), which can lead to substantial losses in both yield quantity and quality. The global agricultural sector consistently grapples with such challenges, with pathogenic infections accounting for an estimated 20–40 % of crop yield losses annually and fungi being responsible for nearly 80 % of plant diseases (4–6). In durian cultivation, root rot disease caused by *Phytopythium vexans* has caused 20–30 % substantial losses in China (7) and 40 % yield reductions for severe cases in Vietnam (8).

Traditional disease management strategies have historically relied on visual inspection (9) and the extensive application of chemical pesticides (10). While visual inspection is accessible, it is often subjective, time-consuming and limited in detecting early-stage or asymptomatic infections. The overuse of fungicides and other chemicals, while effective in the short term, poses significant environmental risks (11), contributes to pathogen resistance (12) and can negatively impact human health (11, 13). More advanced laboratory-based methods, such as polymerase chain reaction (PCR) and enzyme-linked immunosorbent assay (ELISA), offer higher accuracy and sensitivity for pathogen identification (14). However, these techniques typically require specialised expertise, expensive equipment and considerable time, making them impractical for real-time, on-site diagnosis by farmers (15, 16).

The pursuit of sustainable agriculture mandates the adoption of more efficient, precise and environmentally friendly disease management approaches. In recent years, the convergence of technological advancements, particularly in the fields of the internet of things (IoT) and machine learning (ML), has presented a transformative opportunity for plant disease diagnosis (17, 18). This review aims to explore the growing applications of machine learning in enhancing durian disease management. It highlights how ML algorithms can enable more accurate detection, proactive prediction and optimised control of fungal pathogens. We will discuss the current state of research, highlight key methodologies and address the challenges and future prospects of implementing these powerful tools for sustainable durian cultivation.

The landscape of durian disease detection: From conventional to molecular approaches

Effective disease management relies on accurate and timely detection. Historically and still widely in practice, several methods have been employed for identifying fungal pathogens in durian:

Conventional methods: Visual inspection and laboratory analysis

Visual inspection remains the most common and accessible method for detecting fungal diseases in durian. This involves observing the fruit, leaves and stem for visible symptoms such as fruit rot, necrosis, or discoloration (Fig. 1). While straightforward and inexpensive, its accuracy is highly dependent on the observer's experience and it often fails to identify diseases in their incipient stages (9).

Complementing visual assessment, laboratory analysis involves collecting samples and examining them under a microscope to identify fungal structures such as *P. palmivora, F. solani, R. solani and C. gloeosporioides* (2, 3). This method offers greater accuracy and can detect early-stage infections. However, it necessitates skilled microbiologists and specialised equipment, limiting its applicability for rapid, on-site diagnosis in the field.

Molecular-based assays: Polymerase chain reaction (PCR)

Polymerase chain reaction has become a cornerstone molecular method for identifying and detecting fungal diseases in plants. This technique involves extracting genomic DNA from infected plant tissues and amplifying specific target regions using designed primers. The amplified product is then sequenced and compared against organism databases (e.g., using BLAST analysis) for precise identification. For durian, the nuclear ribosomal internal transcribed spacer (ITS) region is commonly amplified for fungal identification.

Studies have successfully used PCR, often with ITS6/ITS4 or ITS1/ITS4 primer combinations, to identify various durian pathogens, including *Phytophthora* and *Pythium* species (19–21), *Pythium cucurbitacearum* (22), *F. solani* and *Lasiodiplodia pseudotheobromae* (23) and *Phytopythium vexans* (8). While highly sensitive and specific, PCR still requires laboratory infrastructure and trained personnel, making it less suitable for immediate field deployment.

Immunology-based methods

Immunology-based approaches leverage serological reactions involving antigens and antibodies for pathogen detection. These methods, including enzyme-linked immunosorbent assay (ELISA), radio-immunosorbent assay (RISA) and tissue blot immunoassay (TBIA), offer advantages in identifying specific proteins or molecules associated with pathogens (24, 25). The combination of immunology-based methods with PCR, such as PCR-ELISA, has shown enhanced sensitivity and rapidity in pathogen detection (26, 27).

While highly specific studies applying these techniques directly to durian diseases are still emerging, the methodology has proven effective for key pathogens that threaten durian cultivation. For example, the *Fusarium solani* which is often associated with root and stem rot in durian. Polyclonal antibodies (PABs) raised against *F. solani* mycelial antigens can be used in various immunological formats, including PTA-ELISA, dot-blot and immunoflorescence where these methods have been effective in detecting *F. solani* in both infected citrus plant tissues and soil (28). While these methods provide valuable diagnostic information, challenges remain, including the complexity of the plant immune system, difficulties in producing highly specific plant antibodies against durian pathogens and the potential for non-target reactions in complex durian tissue samples. This gap highlights the critical need for integrating advanced computational approaches like machine learning.

Machine learning: A paradigm shift in plant disease management for durian

The limitations of traditional and even advanced laboratory methods for rapid, on-site and scalable disease detection have propelled the agricultural sector towards integrating cutting-edge technologies. Machine learning and artificial intelligence (AI) offer a fundamentally different approach to problem-solving, moving beyond pre-programmed rules to learn patterns directly from data. This

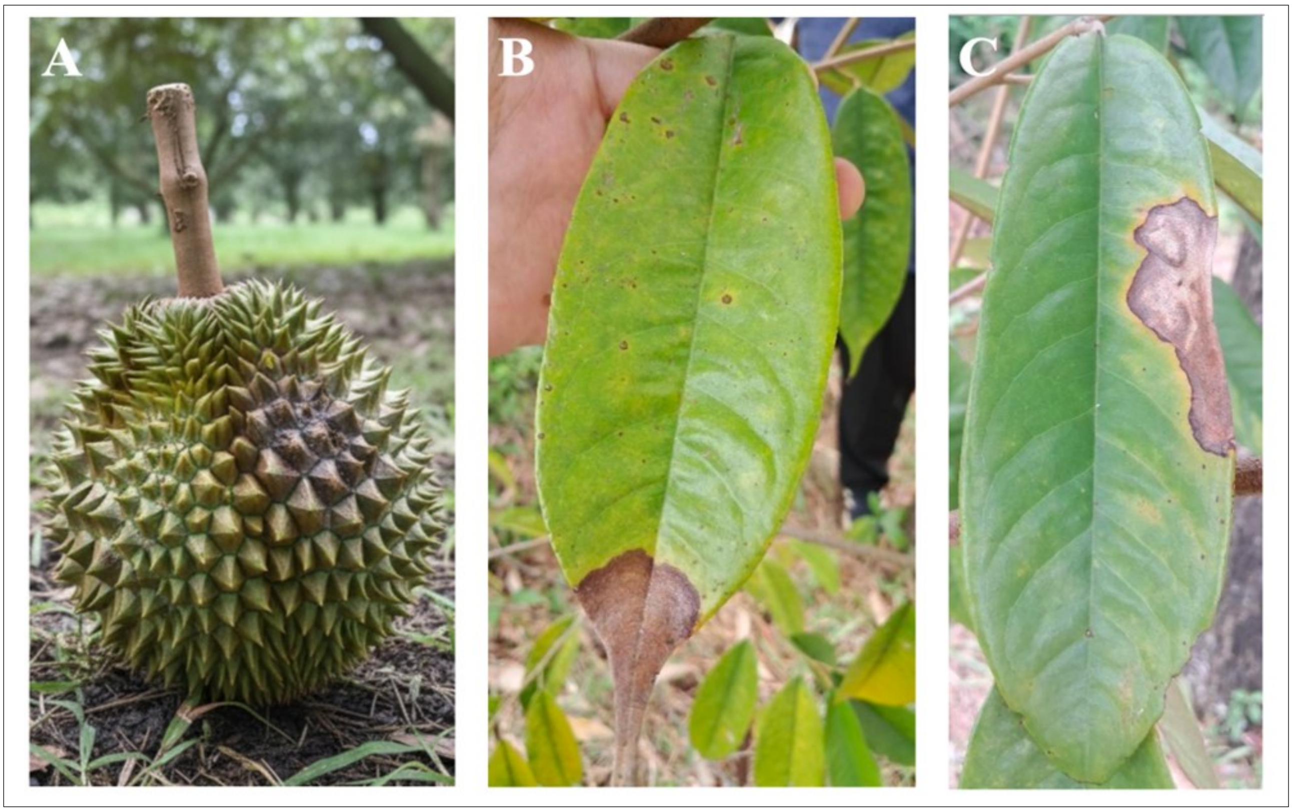

Fig. 1. Fungal diseases in durian cultivation. (A): Fruit rot caused by *Phytophthora palmivora*; (B): Anthracnose caused by *Colletotrichum* spp.; (C): Leaf blight caused by *Rhizoctonia solani*.

paradigm shift holds immense promise for revolutionising durian disease management by enabling faster, more sensitive and highly specific detection (29), ultimately contributing to more sustainable practices by reducing reliance on chemical interventions (30).

Mode of function and technicalities of machine learning

Machine learning is a subfield of artificial intelligence where algorithms are trained to understand patterns and make predictions from data without having to follow explicit programming rules. The fundamental mode of function consists of 3 key steps: feature extraction, model training and optimisation (31).

Feature extraction

This is the process of identifying and isolating the crucial and informative characteristics (features) from raw data. For durian disease detection, raw data includes RGB images of leaves, spectral data and environmental sensor readings. Features extracted might include colour profiles, texture variations and shape anomalies indicative of fungal diseases.

Model training

Machine learning algorithms, such as deep learning architectures (e.g., Convolutional Neural Networks, CNNs) are fed with vast datasets known as “training sets” (32). The learning process is typically defined by 2 technicals paradigms: supervised learning and unsupervised learning.

In supervised learning, the data is labelled beforehand, for example between sick and healthy fruits/leaves. The algorithm then will find the relationship or similarities and differences between individual data that lead them to be labelled as such. Once this relationship is found it is then tested on independent datasets to see how accurate is the relationship that it generates (Fig. 2) (32–34). For durian disease image classification, models like convolutional neural networks (CNNs) can be employed. By recognising subtle cues like unique lesion shapes and early fungal growth on the durian fruit's surface, these models can effectively categorise diseases, enabling a more precise and automated diagnostic process (35–38).

Integrating CNN MobileNets with TensorFlow has created a bridge between advanced technology and practical farming by simplifying durian disease classification (39). These models prioritise efficiency and speed, making them ideal for the resource-limited environments where farmers work (38). Research has shown that these tools can identify symptoms like leaf discoloration and Algal spot with 90 % accuracy, providing a high level of support for on-site diagnosis (39). Ultimately, this approach transforms the smartphone into a vital companion for the farmer, enabling rapid assessments that lead to healthier crops and more sustainable management (40).

Meanwhile, in unsupervised learning, the data is not labelled beforehand and submitted to the algorithm to set it into multiple groups. The algorithm will then separate the data based on the relationship or similarities and differences that it could find. The result can be compared against the original division or label to check on the accuracy of the groupings that the algorithm makes (41, 42). Then, just like in supervised learning, the resulting algorithm or model is tested against another independent data set not used before to see its accuracy. Unsupervised learning is mainly used for identifying hidden patterns or grouping unlabelled data, useful for segmenting durian orchards based on common environmental trends without predefined disease categories (Fig. 3). However, in both methods the independent testing data set sometimes come from the same source that is used for training. Thus, it can still lead to biases even though different individual data are used. This can affect the accuracy of the model when used in the real world (Table 1) (43, 44).

Data limitations for durian-specific models: Data augmentation and transfer learning

Developing reliable diagnostic tools for durian is often hindered by the scarcity of high-quality, diverse datasets, which are difficult to collect in active orchard environments (45). To bridge this gap, researchers employ data augmentation, a process of digitally diversifying existing durian images through geometric shifts, lighting adjustments and synthetic generation to give models a broader "experience" of what a diseased leaf might look like (40–42). It is essential, however, that these augmented images are used only during the training phase to ensure the model’s performance is accurately measured against real-world durian samples (31, 42).

Since specific durian data is often limited, transfer learning provides a way to leverage "pre-learned" knowledge from massive general datasets, which is then fine-tuned to recognize unique

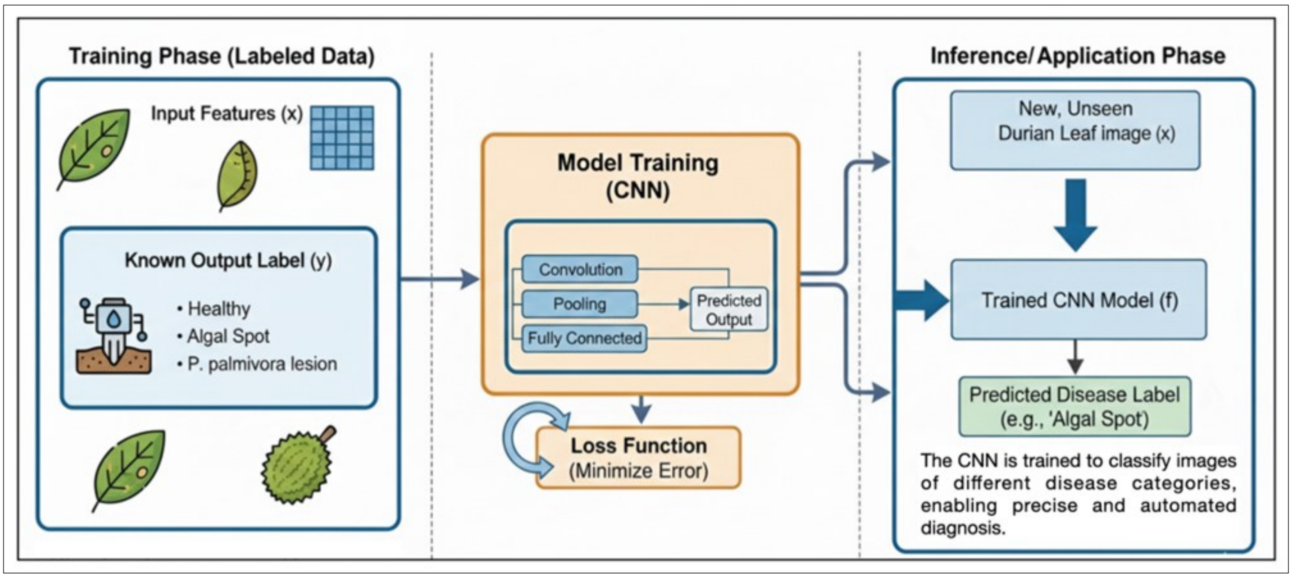

Fig. 2. Supervised learning pipeline for an automated durian disease detection. CNN learns to associate leaf features with specific disease labels, repeatedly improving its accuracy during training. Once optimized, the model applies these learned patterns to provide rapid, automated diagnoses for new, unseen images during the inference phase.

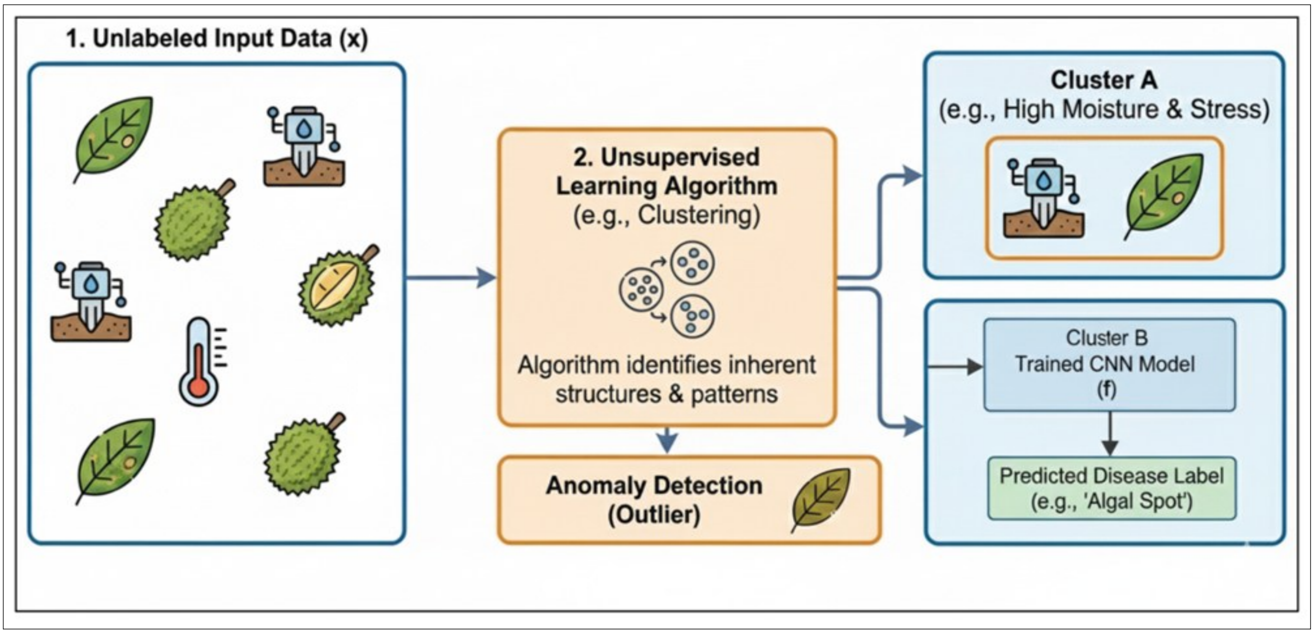

Fig. 3. Unsupervised learning pipeline for an automated durian disease detection. The system analyses unlabelled, multi-source data, such as leaf images and sensor readings, to identify hidden structures and patterns. By clustering similar data and isolating anomalies, the technique converts raw field observations into a structured format, allowing a trained CNN to deliver exact, automated diagnoses.

Table 1. Potential applications of machine learning for early detection of various durian diseases

Aspect	Supervised learning	Unsupervised learning
Data requirement	Requires labelled data	Works with unlabelled data
Applications	Classification, regression	Clustering, dimensionality reduction
Accuracy	Generally higher due to labeled data	Generally lower due to lack of labels
Interpretability	Easier to interpret	Harder to interpret
Flexibility	Less flexible due to need for labelled data	More flexible with data availability
Risk of overfitting	Higher	Lower

durian pathologies (43, 46). This method has successfully powered mobile applications that bring expert-level diagnostic capabilities directly to the farm, helping bridge the gap between complex computer science and daily agricultural work (30, 44).

Despite these technical solutions, a significant challenge remains: a model that excels in a controlled laboratory setting can often falter when faced with the unpredictable conditions of a real durian grove, such as shifting sunlight, varying tree ages, or different durian cultivars (30, 44). To build tools that farmers can truly trust, it is paramount to develop open-access datasets that capture the full, messy reality of the orchard. This ensures that the technology serves as a dependable companion for farmers, helping them protect their crops and their livelihoods with greater confidence (30, 44).

Integrating internet of things and advanced sensing for enhanced machine learning applications

While visual monitoring is a cornerstone of durian farming, relying solely on visible symptoms often means pathogens are already well-established (16). To move toward proactive care, integrating IoT technologies and advanced sensors is essential. Biosensors, for instance, can detect specific fungal markers or biochemical changes in durian trees-such as those associated with systemic diseases like stem canker-long before physical lesions emerge (47, 48). These devices provide rapid, low-cost data that serves as a vital early-warning signal for machine learning models (16).

Beyond the reach of the human eye, hyperspectral and thermal imaging can identify cellular damage and physiological stress in durian groves by capturing infrared wavelengths sensitive to early-stage infection (49). When combined with environmental sensors tracking orchard humidity, temperature and soil moisture, these tools create a multi-dimensional dataset that allows ML algorithms to predict outbreaks before they spread. This transition to "predictive" farming ensures that resources like fungicides are used only where and when they are truly needed, reducing costs and environmental impact (49).

For this technology to be truly transformative for the farmer, it must function where the work happens– in the orchard. Shifting from cloud-based systems to edge computing using lightweight models like MobileNets on smartphones or drones enables real-time, on-site diagnosis even in areas with limited connectivity (37, 39). By integrating these diagnostic tools into a broader integrated pest and disease management (IPDM) strategy, farmers are no longer just reacting to disease; they are empowered with the foresight to protect their livelihoods more sustainably and efficiently.

Conclusion

Securing the future of durian cultivation, a crop central to the heart and economy of Southeast Asia requires a shift from simply reacting to disease toward a more supportive, technological partnership. For too long, farmers have relied on visual checks that are often subjective or laboratory tests that are far too slow for the field; however, the rise of machine learning offers a more practical path forward. By putting the power of advanced algorithms like CNNs directly into the hands of farmers through smartphones, we can now identify devastating fungal threats with up to 90 % accuracy. When these digital tools are paired with "predictive" sensors like thermal imaging and IoT devices, they act as an early-warning system, spotting invisible stress before a single lesion even appears. Although the "messy reality" of an active orchard makes data collection difficult, techniques like transfer learning help bridge the gap between complex computer science and daily agricultural labor.

Ultimately, this move toward edge computing and smart diagnostics is not just about the technology itself; it is about empowering farmers with the foresight to protect their livelihoods sustainably. By using these tools to optimise resource allocation and reduce our reliance on chemical pesticides, we ensure a healthier, more resilient durian industry for generations to come.

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Authors' contributions

NSAA contributed to the concept of the paper and took the lead in writing, reviewing and editing the manuscript. ZZ and NHS contributed to writing, review and editing of the manuscript. NHNH, PCK and AR contributed to the review and editing of the manuscript. NAA contributed to the concept of the paper, as well as review and editing of the manuscript. All authors read and approved the final manuscript.

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