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A Survey on Deep Learning-Based Stress Detection and Classification in Arecanut Trees for Precision Crop Health Monitoring

Madhu B G1, Patil N S2, Vinutha H P3

1Assistant Professor, Department of CSBS, Bapuji Institute of Engineering and Technology, Davanagere madhu17gowdru@gmail.com
2Associate Professor, Department of IS&E, Bapuji Institute of Engineering and Technology, Davanagere patilbathi@gmail.com
3Professor and Head, Department of IS&E and CSBS, Bapuji Institute of Engineering and Technology, Davanagere vinuprasad.hp@gmail.com

ABSTRACT: Arecanut cultivation is an economically important agricultural activity in many tropical regions; however, crop productivity is frequently threatened by a wide range of biotic and abiotic stress factors, including diseases, pest infestations, nutrient deficiencies, drought, and environmental fluctuations. Early identification of these stress conditions plays a significant role in mitigating crop yield losses and improving crop management practices. Recent progress in Machine Learning (ML), Artificial Intelligence (AI), and Deep Learning (DL) has enabled the development of automated systems capable of detecting plant stress with high accuracy using image-based and sensor-driven data. This paper presents a survey of recent studies employing Convolutional Neural Networks (CNNs), hyperspectral imaging, Vision Transformers (ViTs), UAV-based sensing, transfer learning models and multimodal learning approaches for stress detection and crop health monitoring. Existing methodologies are analyzed with respect to their performance, strengths, and limitations. Despite significant advancements, challenges such as limited annotated datasets, environmental variability, computational complexity, and inadequate real-field validation continue to hinder practical deployment. Emerging technologies including Explainable AI (XAI), Internet of Things (IoT)-based monitoring, edge computing, and precision agriculture offer promising opportunities for improving detection accuracy and scalability. The survey highlights current research trends, existing challenges, and future directions for developing reliable and efficient arecanut stress detection systems.

1. INTRODUCTION

Agriculture is increasingly adopting advanced digital technologies to improve productivity, sustainability, and crop management practices. The adoption of Artificial Intelligence (AI), Deep Learning (DL), Machine Learning (ML), and Computer Vision has greatly improved traditional monitoring by enabling automated analysis of crop health and stress conditions. These intelligent technologies support early diagnosis of plant disorders, reduce dependence on manual inspection, and facilitate data-driven decision-making in precision agriculture. Consequently, extensive research has focused on developing automated systems for recognizing plant diseases and stress conditions across diverse crop species.

The growing demand for sustainable agricultural production has accelerated the development of intelligent monitoring systems capable of processing large volumes of agricultural data. Recent advancements in sensing technologies, image acquisition systems, remote sensing platforms, and cloud computing have enabled continuous monitoring of crop conditions at different spatial and temporal scales. These developments have created new opportunities for integrating advanced computational techniques into agricultural management practices, thereby improving operational efficiency and resource utilization.

In parallel, deep learning architectures have achieved remarkable success in various computer vision applications, including image classification, object detection, segmentation, and pattern recognition. Their ability to automatically learn discriminative features from complex datasets has encouraged widespread adoption in agricultural research. Convolutional Neural Networks (CNNs), transfer learning models, attention-based architectures, Graph Neural Networks (GNNs), and Vision Transformers (ViTs) have emerged as powerful tools for analyzing agricultural imagery and extracting meaningful information for automated decision-making. The integration of these techniques with multimodal data sources has further expanded their applicability in modern farming systems.

The increasing number of research contributions in this field has resulted in a diverse range of methodologies, datasets, evaluation metrics, and implementation strategies. While many studies report promising results, differences in experimental settings and performance assessment often make direct comparison difficult. Therefore, a comprehensive synthesis of existing research is essential to provide a consolidated understanding of current advancements, methodological trends, and technological developments. Such an analysis can support researchers and practitioners in identifying effective approaches, addressing existing challenges, and guiding future innovations in intelligent crop monitoring and agricultural automation.

1.1 Background

Arecanut (Areca catechu L.) is one of the most important plantation crops cultivated in tropical and subtropical regions, particularly in India. The crop contributes significantly to farmers' income and the agricultural economy. However, arecanut production is frequently affected by various biotic and abiotic stress factors, including diseases, pest infestations, nutrient deficiencies, drought, and environmental fluctuations, which can substantially reduce crop yield and quality [11], [12], [13]. Traditionally, stress identification in arecanut plantations relies on manual field inspection and expert assessment. Although effective to a limited extent, these methods are labor-intensive, time-consuming, and often unsuitable for large-scale monitoring [11], [12]. Recent advances in Artificial Intelligence (AI), Deep Learning (DL), Computer Vision and Machine Learning (ML) have enabled the advancement of automated systems for plant health monitoring and stress detection [2], [12], [13]. Advanced technologies such as Convolutional Neural Networks (CNNs), transfer learning models, hyperspectral imaging, and UAV-based sensing systems have demonstrated considerable effectiveness in the early detection of crop stress and disease conditions [1], [2], [18], [25]. These developments highlight the growing potential of intelligent agricultural systems for improving crop management, enhancing productivity, and supporting sustainable farming practices.

1.2 Motivation and Research Gap

Recent advances in Artificial Intelligence (AI), Deep Learning (DL), and Machine Learning (ML) have significantly improved plant stress identification and crop health monitoring systems. Numerous studies have demonstrated the potential of Convolutional Neural Networks (CNNs), hyperspectral imaging, transfer learning models, Vision Transformers (ViTs) and UAV-based sensing technologies for plant disease diagnosis and stress detection [1], [13], [18], [25]. These approaches enable automated, accurate, and non-destructive crop monitoring, thereby supporting the advancement of precision agriculture systems.

Despite these developments, studies focusing specifically on arecanut stress detection remain relatively limited compared to other major agricultural crops. Most existing studies primarily address disease classification, while abiotic stresses such as drought, nutrient deficiency, temperature fluctuations, and waterlogging receive comparatively less attention [11], [12], [13], [21]. Furthermore, many models are designed and assessed using small or controlled datasets, limiting their capacity to generalize under diverse field conditions [2], [4], [10].

Another important limitation is the shortage of comprehensive reviews that thoroughly examine both biotic and abiotic stress detection approaches for arecanut cultivation [12], [13], [21]. Existing surveys often focus on specific diseases, individual deep learning techniques, or general agricultural applications without providing a consolidated perspective on arecanut stress monitoring [12], [13], [21]. In addition, challenges related to dataset availability, model interpretability, real-time deployment and implementation, and the incorporation of precision agriculture technologies remain insufficiently addressed [4], [12], [13], [18].

Therefore, a systematic review is required to summarize recent developments, compare existing approaches, identify knowledge gaps, and outline prospective approaches for creating reliable and scalable arecanut stress detection systems. This review aims to bridge this gap by providing a detailed analysis of current AI-driven approaches and their prospective applications in sustainable arecanut cultivation.

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1.3 Major Contributions of the Review

- This review presents a thorough review of Machine Learning (ML), Deep Learning (DL), and Deep Convolutional Neural Networks (DCNNs) techniques applied to arecanut stress detection and crop health monitoring [2], [8], [11], [12].
- A comparative analysis of image processing, transfer learning, attention-based models, Vision Transformers, and other deep learning approaches is presented to evaluate their effectiveness in stress detection applications [1], [3], [13], [18], [24].
- The study identifies current research gaps in monitoring both biotic and abiotic stress conditions, particularly with a focus on arecanut cultivation [12], [13], [21].
- Key issues associated with dataset availability, model generalization, computational complexity, and real-world deployment in precision agriculture are discussed [4], [12], [13], [18].
- Future research trends, including Explainable Artificial Intelligence (XAI), multimodal learning, Vision Transformers, IoT-enabled monitoring systems, and precision agriculture technologies, are explored to support future advancements in arecanut stress detection [3], [5], [13], [15].

2. ARECANUT STRESS CONDITIONS

Arecanut plants are frequently exposed to multiple stress conditions that affect their growth, development, yield, and overall productivity. These stress factors are commonly grouped into two major groups: biotic stress and abiotic stress. Biotic stress results from the activity of living organisms such as fungi, bacteria, viruses, insects, nematodes and pests, which can cause diseases and damage plant tissues. In contrast, abiotic stress arises from unfavorable environmental and physical conditions, including drought, excessive moisture, temperature fluctuations, salinity, and nutrient deficiencies. Both types of stress can significantly affect the physiological functions and health of arecanut plants, leading to reduced crop quality and economic losses. Figure 1 presents the classification of major biotic and abiotic stress conditions affecting arecanut cultivation.

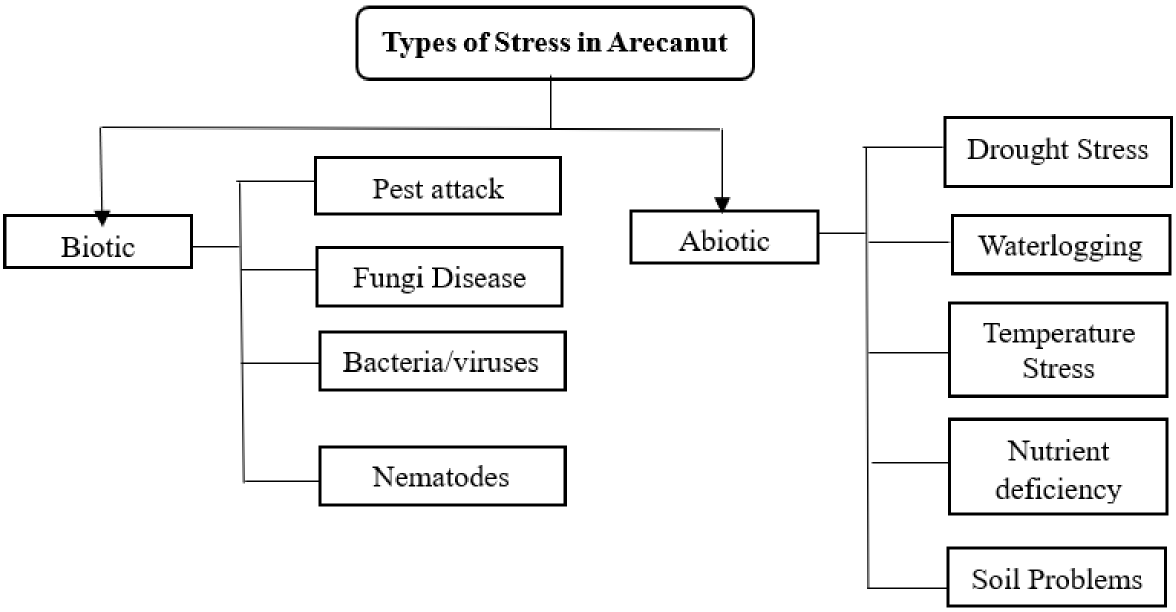
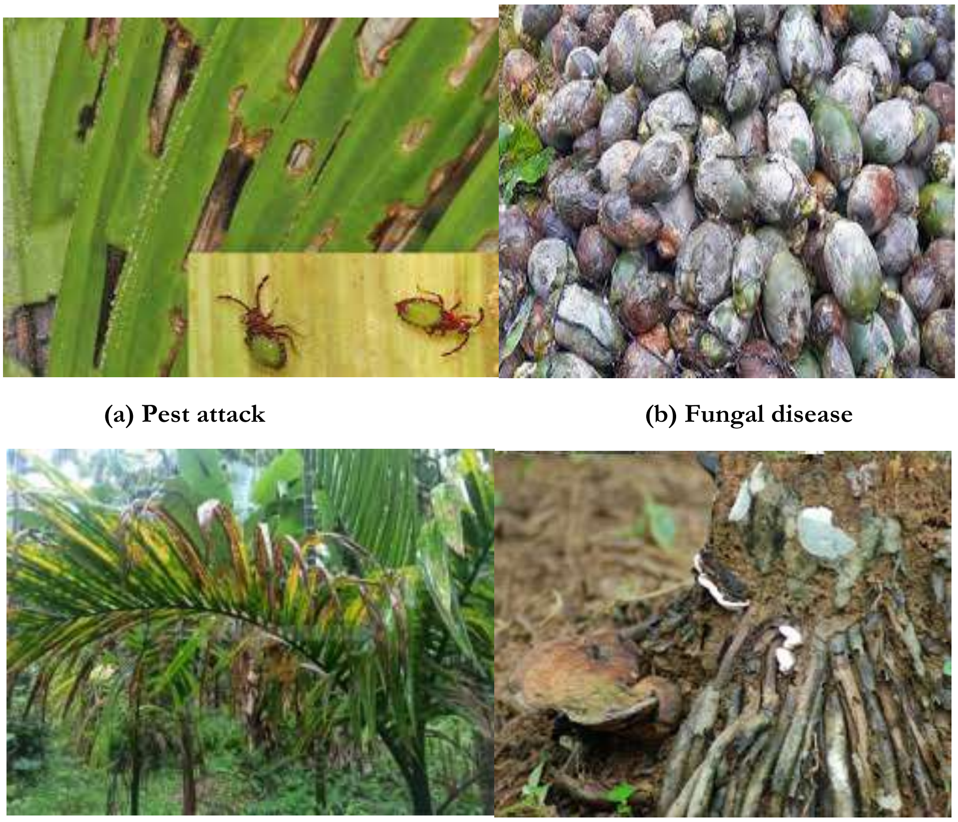


Figure 1. Classification of biotic and abiotic stresses in arecanut plants.

Table 1 presents the major stress conditions affecting arecanut plants and their symptoms. The stress conditions include diseases, pest attacks, environmental factors, and nutrient deficiencies. The table provides a brief description of the symptoms associated with each stress condition and helps in their identification and management in arecanut cultivation.

Table 1. Arecanut stress conditions and their characteristic symptoms.

Category	Stress Type	Disease / Problem	Symptoms
Biotic	Pest attack	Spindle bug, root grub, red palm weevil	Damaged leaves, holes in stem, weak roots, plant wilting
	Fungal disease	Fruit rot (Koleroga), bud rot, leaf spot	Rotting of nuts, crown death, leaf spots
	Bacteria/virus	Bacterial leaf stripe, yellow leaf disease	Yellowing leaves, streaks on leaves, reduced yield
	Nematodes	Root-knot disease	Swollen roots, stunted growth, poor nutrient uptake
Abiotic	Drought stress	Water deficiency disorder	Wilting, leaf drying, nut shedding
	Waterlogging	Root damage	Yellowing, root rot, poor growth
	Temperature stress	Heat/cold injury	Leaf scorch, drying or damage of tissues
	Nutrient deficiency	Chlorosis, poor growth	Yellow leaves, low yield, weak plants
	Soil problems	Salinity, poor drainage	Stunted growth, root damage



(a) Pest attack **(b) Fungal disease**

(c) Bacteria/virus **(d) Nematodes**

Figure 2. Representative biotic stresses affecting arecanut

Figure 2 illustrates representative examples of major biotic stresses affecting arecanut cultivation. Figure 2(a) shows pest attack,

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which is one of the most common causes of crop damage in arecanut plantations. Figure 2(b) presents fungal disease infection, while Figure 2(c) depicts bacterial or viral infection, both of which can adversely affect plant health and productivity. Figure 2(d) represents nematode infestation, which poses a significant threat to root development and nutrient uptake. Together, these biotic stresses highlight the diverse challenges associated with arecanut crop management and emphasize the need for effective monitoring and early detection strategies.

(a) Drought stress

(b) Nutrient deficiency

(c) Waterlogging stress

(d) Temprature stress

Figure 3. Representative abiotic stresses affecting arecanut

Figure 3 illustrates representative examples of major abiotic stresses affecting arecanut cultivation. Figure 3(a) shows drought stress resulting from insufficient water availability, while Figure 3(b) depicts nutrient deficiency caused by inadequate essential nutrients for plant growth. Figure 3(c) presents waterlogging stress, which occurs due to excess soil moisture and poor drainage conditions. Figure 3(d) represents temperature stress arising from unfavorable temperature variations. Together, these abiotic stresses can adversely affect plant growth, yield, and overall crop productivity, emphasizing the importance of effective monitoring and management practices.

3. LITERATURE REVIEW

Understanding the various biotic and abiotic stress conditions affecting arecanut plants is vital for establishing effective monitoring and management strategies. Over the past few years, extensive research has focused on a wide range of Artificial Intelligence (AI), Deep Learning (DL), remote sensing, image processing, and Machine Learning (ML) techniques to automate stress detection and improve crop health assessment. The following section reviews the existing literature on arecanut stress detection and related agricultural stress monitoring approaches, highlighting their methodologies, performance, strengths, and limitations.

Saber Mehdipour et al. [1] The study offered an in-depth review of Vision Transformer (ViT) applications in precision agriculture. It examined approximately 50 ViT-based agricultural research works focusing on plant disease detection, crop monitoring, classification, segmentation, and yield prediction. It compares traditional CNN architectures with ViTs and hybrid CNN–ViT models, highlighting the superior capability of ViTs in capturing long-range dependencies and complex visual patterns. The study also discusses obstacles such as dataset limitations, computational cost, interpretability, and field-level deployment, while identifying future research directions for intelligent agricultural systems.

Finney Daniel Shadrach et al. [2] the paper proposes a deep learning architecture combining Graph Neural Networks (GNN) and the Bat Algorithm (BA) for arecanut disease detection. The model uses leaf images collected under real farm conditions and detects multiple diseases with high accuracy. The proposed GB model achieved 98.45% accuracy, outperforming traditional CNN and hybrid models. The investigation also reduces processing time and improves hyperparameter optimization for real-time agricultural applications. However, the work is limited by a small dataset and reliance on RGB images only.

Sanjyot Patil et al. [3] developed a plant stress detection framework using thermal imagery and a Global Context Vision Transformer (GCViT). The model was benchmarked against multiple CNN architectures and achieved high predictive accuracy between 93% and 97%. Explainable AI techniques were employed to generate heatmaps highlighting stress-affected regions, improving model transparency and trustworthiness. The proposed approach offers an effective non-invasive solution for early stress diagnosis and precision agriculture applications.

Komal Sharma et al. [4] reviewed recent AI-based techniques for detecting abiotic stresses in crops. The study covers advanced sensing technologies including hyperspectral imaging, thermal cameras, IoT devices, drones, and satellite systems combined with machine learning and deep learning models. The authors conclude that AI-assisted monitoring enables early, accurate, and non-destructive stress detection, supporting precision agriculture and sustainable crop management. The review also highlights challenges related to data quality, model explainability, and real-world deployment.

S. Patil et al. [5] developed a multimodal AI framework using a Multi-Modal Vision Transformer (MMViT) for plant stress classification. The model integrates RGB and thermal images to capture complementary stress-related information and achieved 94.3% accuracy, outperforming single-modality Vision Transformer models. The study also contributes a publicly available thermo-RGB dataset containing over 4,000 labeled images. The proposed multimodal approach demonstrates the potential of combining multiple sensing modalities for robust and early plant stress detection in precision agriculture.

Aswini Kumar Patra et al. [6] A CNN-LSTM spatio-temporal deep learning model was proposed to classify nitrogen stress severity in plants under combined stress conditions. The model integrated RGB, multispectral, and infrared time-series images, capturing both spatial and temporal stress patterns. It achieved a high classification accuracy of ~98%, outperforming CNN-only and traditional machine learning models. The study demonstrates that combining spatial and temporal deep features enables rapid and precise detection of nutrient stress, supporting precision crop management and proactive intervention.

Nijhum Paul et al. [7] The paper provides a systematic and comprehensive review of deep learning (DL) methods applied to plant stress detection, covering key components such as image acquisition, preprocessing, and DL architectures including CNNs (VGG16, ResNet50, Inception), Vision Transformers (ViT), and hybrid CNN-Transformer models, as well as self-supervised learning (SSL) and few-shot learning (FSL) techniques. Most models rely on RGB and multispectral image data, with data augmentation and multimodal inputs improving performance. Reported accuracies vary depending on dataset and stress type, typically ranging from 85% to 98%, with hybrid or transformer-based models achieving the highest precision for complex or overlapping stress symptoms. The review also discusses challenges such as data scarcity, generalizability, and overlapping stress signatures, and highlights future directions for scalable, real-field plant stress detection using robust, adaptive DL algorithms.

K. Beena et al. [8] This paper presents a customized CNN model for recognizing diseases in arecanut plants using image data. It uses a dataset of 4,800 field images covering healthy and diseased categories such as Mahali, stem bleeding, stem cracking, and yellow leaf. The model includes multiple convolutional layers with preprocessing techniques like resizing and normalization to improve performance. It achieved a high accuracy of 97.33% with strong precision and recall across all classes. Compared to traditional machine learning and existing CNN models, it performs significantly better. The system can be deployed using web interfaces and IoT devices for real-time agricultural monitoring.

R. Dhanya et al. [9] The study reviews various deep learning techniques for tomato leaf disease detection, highlighting the performance of convolutional neural networks (CNNs) and attention-based models in improving classification accuracy. Prior works such as attention-guided CNNs, multi-scale attention networks, and self-attention models have achieved high accuracies ranging from approximately 94% to 98.9%, demonstrating strong performance in recognizing disease patterns. Lightweight attention-based models have also been created for real-time detection on mobile devices, ensuring computational efficiency. Additionally, research highlights the importance of large and diverse datasets to enhance model generalization and robustness. Overall, the literature suggests that the integration of attention mechanisms into deep learning models substantially increases the accuracy and reliability of crop health monitoring in precision agriculture.

Hassan Rezvan et al. [10] This study proposes a fully automated framework for segmenting rice seedlings using the Segment Anything Model (SAM) and assessing their health through unsupervised anomaly detection with multi-modal features (morphological, spectral, and textural). Unlike traditional supervised plant segmentation methods that rely on large labeled datasets, the SAM-based approach achieves high segmentation performance (mean Dice scores up to ~94.7%) and effective clustering of healthy versus stressed seedlings using One-Class SVM, demonstrating scalable crop health monitoring without manual annotation. The research highlights the benefits of combining foundation models with unsupervised learning in precision agriculture for analyzing rice seedling conditions across multiple growth stages.

Kiran Kumar B. S. et al. [11] proposed a deep learning- driven framework for automated areca nut disease recognition using CNN-based models. The authors developed a dataset containing 1,332 areca nut images representing four disease categories: button shedding, fruit rot, fruit crack, and exfoliation. Five pre-trained deep learning models—VGG16, DenseNet121, MobileNetV3-Large, ResNet50, and ResNet18—were evaluated for disease classification. Among these models, ResNet18 achieved the highest accuracy of 98.12% with a very low inference time of 0.334 ms, demonstrating its suitability for practical agricultural applications. The study demonstrates the effectiveness of transfer learning and lightweight CNN architectures for accurate disease diagnosis. However, the dataset size is relatively limited, and the model was evaluated primarily on image data collected under controlled conditions, which may affect its generalization to diverse field environments.

Ashwini S. P. et al. [12] conducted a comprehensive survey on deep learning applications in arecanut research. The study reviews CNNs, transfer learning models, image processing techniques, and AI-based disease detection systems used for arecanut crop monitoring. It highlights challenges such as limited datasets, environmental variability, and deployment issues while suggesting future directions including IoT integration, multimodal learning, and computationally efficient deep learning models in precision agriculture.

Muhammad A. et al. [13] The study presents a comprehensive survey of crop stress detection techniques, covering both biotic and abiotic stresses and their associated physiological indicators. The authors compare traditional destructive methods with modern non-destructive approaches such as hyperspectral imaging, chlorophyll fluorescence, thermal imaging, spectroscopy, LiDAR, UAV-based sensing, and IoT-enabled monitoring systems. The review further discusses the combination of Machine Learning (ML), Deep Learning (DL), CNNs, LSTMs, Random Forest, SVM, XGBoost, and Vision Transformers (ViTs) for automated stress detection and prediction. The study highlights that ML-assisted non-destructive sensing enables accurate, scalable, and real-time crop monitoring for precision agriculture. However, limitations such as high sensor costs, data complexity, model generalization, and the requirement for large annotated datasets remain significant barriers to practical deployment.

Md Ismail Hossen et al. [14] reviewed the application of transfer learning in agriculture and highlighted its effectiveness in addressing limited labeled data problems. The study examines various pre-trained CNN architectures including VGG, ResNet, DenseNet, and Inception for agricultural image classification tasks such as disease detection, pest recognition, and nutrient deficiency assessment. The authors concluded that transfer learning improves model accuracy and training efficiency; however, challenges associated with domain adaptation, negative transfer, and dataset diversity remain. They also identified agricultural foundation models, few-shot learning, and zero-shot learning as promising directions for future research.

Aswini Kumar Patra et al. [15] proposed an explainable Vision Transformer-based framework for drought stress identification using aerial imagery of potato crops. The study integrates ViT-based models with Support Vector Machine (SVM) classification and transfer learning to enhance stress detection performance. The model incorporates attention-map visualization to explain predictions, making the framework more interpretable than conventional deep learning approaches. The results demonstrate high drought stress detection capability while supporting transparent decision-making for precision agriculture applications.

N. S. Vidhya Shree et al. [16] This study utilizes transfer learning with the ResNet-50 model to derive deep features from areca nut leaf images for disease detection, comparing the efficiency of CNN and SVM classifiers. Leveraging pre-trained weights allows effective training despite limited datasets, with the ResNet-50 + SVM approach achieving high classification accuracy, often above 90%. The research demonstrates that transfer learning combined with traditional classifiers can offer a reliable, scalable, and automated method for early detection of areca nut diseases, aiding precision agriculture and reducing dependency on manual inspections.

Lian Lei et al. [17] presented "Deep Learning Implementation of Image Segmentation in Agricultural Applications: A

Comprehensive Review." The paper provides a detailed review of deep learning-based image segmentation techniques used in agriculture, including U-Net, Generative Adversarial Networks (GANs), Mask R-CNN, Transformer-based models, Graph Neural Networks (GNNs) and attention-based architectures. The authors categorize segmentation methods into eight major groups and discuss their applications in plant disease detection, weed identification, crop growth monitoring, yield estimation, and crop counting. The review highlights that image segmentation enables precise localization of diseased regions and stress symptoms, improving the accuracy of agricultural monitoring systems. The study also discusses publicly available datasets, evaluation metrics, issues associated with labeling inconsistencies and complex field conditions, and potential directions for future research in agricultural image segmentation.

Kun Zhang et al. [18] presented "The Application of Hyperspectral Imaging for Wheat Biotic and Abiotic Stress Analysis: A Review." The paper conducts a comprehensive examination of hyperspectral imaging (HSI) applications for detecting both biotic and abiotic stresses in wheat. More than 200 peer-reviewed studies were analyzed, covering stress conditions such as drought, salinity, nutrient deficiencies, temperature stress, fungal diseases, and pest infestations. The authors discuss hyperspectral sensing platforms deployed in laboratory, greenhouse, UAV, and field environments, along with the integration of ML and DL techniques for stress classification. The review highlights the potential of HSI to enable non-destructive and early stress detection before visible symptoms appear. However, challenges including high-dimensional data processing, sensor costs, limited labeled datasets, and real-world deployment complexity remain significant barriers.

Lei Zhang et al. [19] The study applies machine learning algorithms for assessing maize seedling traits under drought stress, identifying key growth parameters affected by water deficiency. Algorithm such as Random Forest and XGBoost are applied for prediction, with XGBoost achieving strong accuracy (AUC $\approx$ 0.993) in classifying drought tolerance. The research concludes that machine learning offers an efficient and reliable approach for drought stress assessment and supports precision breeding in agriculture.

Sarah E. Jones et al. [20] The study applied a random forest machine-learning model using multi-sensor (RGB, NIR, red-edge, SWIR) and multi-temporal UAV data to phenotype drought stress in soybean, achieving a classification accuracy of ~76.2% for the highest accuracy model distinguishing stress classes. The proposed model used selected vegetation indices and spectral bands to enable early, pre-visual detection of water-limiting stress before traditional visual symptoms appeared. Results suggest that integrating diverse spectral data with machine learning provides a robust high-throughput pipeline for drought stress monitoring, improving screening efficiency in breeding and precision crop management.

Sèton Calmette Ariane Houetohossou et al. [21] The review study explores deep learning approaches for disease detection and for classifying biotic stresses such as fungal, bacterial, and viral infections, as well as abiotic stresses including nutrient deficiency, water stress, and light stress in fruits and vegetables, highlighting the dominant use of Convolutional Neural Networks (CNNs) in agricultural stress detection tasks. It synthesizes findings from 132 relevant studies (2003–2022), showing that GoogleNet, ResNet50, and VGG16 are among the most frequently used architectures and that most datasets originate from field and online sources. The review also identifies key challenges—such as data imbalance, small datasets, and limited studies on abiotic stress detection—and suggests future research directions including larger, diverse datasets and models that better generalize to real field conditions.

Kushalatha M. R et al. [22] This study employs hyperspectral imaging combined with machine learning to classify arecanut leaf samples according to disease severity by analyzing variations in spectral reflectance between healthy and infected plants. Among the classifiers tested, the Light Gradient Boosting Machine (LightGBM) achieved the highest accuracy, effectively predicting disease levels. The study concludes that hyperspectral analysis provides a reliable tool for monitoring arecanut crop health, enabling timely intervention and supporting improved yield and disease mitigation strategies.

Mamatha Balipa et al. [23] The paper Arecanut Disease Detection Using SVM Algorithms and CNN proposes an automated system to detect arecanut diseases using image processing, CNN, and SVM algorithms. The authors collected 181 healthy and diseased arecanut images from Karnataka and applied image preprocessing and data enhancement techniques before training the models. CNN automatically extracted features from images, while SVM used texture features such as GLCM and Gabor filters. The results showed that CNN achieved better accuracy (90%) compared to SVM (75%) in classifying healthy and diseased arecanuts. The study helps farmers identify diseases early and reduce manual inspection efforts.

Poornima Singh Thakur et al. [24] proposed "Explainable Vision Transformer Enabled Convolutional Neural Network for

Plant Disease Identification: PlantXViT." The study introduced a lightweight hybrid deep learning architecture that combines CNN feature extraction with Vision Transformer (ViT) self-attention mechanisms for plant disease classification. The proposed PlantXViT model contains only 0.85 million trainable parameters, making it suitable for IoT-enabled smart agriculture systems. The model was evaluated on five public plant disease datasets and achieved accuracies of 93.55% (Apple), 92.59% (Maize), 98.33% (Rice), and 98.86% (PlantVillage). Additionally, Explainable AI methods such as Grad-CAM and LIME were employed to visualize disease regions and improve model interpretability. The study demonstrates that combining CNNs with Vision Transformers enhances classification accuracy and explainability in agricultural disease detection.

Shuhan Lei et al. [25] This study explores the application of UAV-based multispectral remote sensing to detect yellow leaf disease in arecanut, providing a quantitative alternative to traditional visual inspection. Vegetation indices like NDVI and GNDVI are extracted and analyzed using machine learning models for disease severity classification. The research also correlates disease severity with living vegetation volume (LVV) through 3D UAV data, demonstrating precise monitoring and spatial analysis for improved crop management.

3.1 Overview of Existing Studies

Recent advancements in Machine Learning (ML), Deep Learning (DL), and Artificial Intelligence (AI) have significantly improved automated plant stress detection and crop health monitoring systems [7], [12], [13]. Researchers have explored various techniques, including Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), hyperspectral imaging, transfer learning models, ,thermal imaging, and UAV-based sensing technologies for the detection of plant diseases and stress conditions [1], [3], [13], [18], [25]. These approaches enable efficient feature extraction, accurate classification, and early stress diagnosis, thereby supporting precision agriculture and sustainable crop management practices [3], [4], [13], [18].

Several studies have specifically focused on arecanut disease detection using image processing and deep learning techniques [2], [8], [11], [16], [22], [23]. In addition, numerous research efforts have investigated advanced sensing technologies, multimodal learning frameworks, explainable AI methods, and transformer-based architectures for stress detection in agricultural crops [1], [3], [5], [15], [24]. The reviewed studies demonstrate substantial progress in automated stress monitoring; however, challenges related to dataset availability, model generalization, interpretability, and real-world deployment remain significant concerns [4], [7], [12], [13], [18].

3.2 Comparative Analysis of Existing Studies

Table 2. Comparative Analysis of Existing Studies on Arecanut Stress Detection and Crop Health Monitoring.

Ref.	Author(s) & Year	Paper Title	Methodology	Accuracy (%)	Advantages	Limitations
[1]	Mehdipour et al. (2026)	Vision Transformers in Precision Agriculture: A Comprehensive Survey	Vision Transformer Survey	N/A	Comprehensive analysis of ViT applications	High computational complexity
[2]	Shadrach et al. (2026)	Efficient Deep Learning Framework for Arecanut Disease Detection Using Graph Neural Network and Bat Algorithm	GNN + Bat Algorithm	98.45	High accuracy and optimized learning	Small dataset

[3]	Patil and Kolhar (2026)	Enhancing Plant Stress Diagnosis Using Thermal Imagery and Global Context Vision Transformer with Explainable AI Approach	GCViT + Thermal Imaging + XAI	93–97	Explainable and accurate stress detection	Limited stress categories
[4]	Sharma et al. (2026)	Artificial Intelligence-Assisted Detection of Abiotic Stress in Agricultural Crops	AI, ML, DL Review	N/A	Comprehensive overview of sensing and AI methods	Practical deployment challenges
[5]	Patil et al. (2026)	Multimodal AI for Plant Stress Classification Across Multiple Plant Species	MMViT	94.3	Robust multimodal classification	Requires multiple sensors
[6]	Patra and Sahoo (2025)	Improved Classification of Nitrogen Stress Severity in Plants Under Combined Stress Conditions	CNN-LSTM	~98	Captures spatial and temporal features	Computationally intensive
[7]	Paul et al. (2025)	Deep Learning for Plant Stress Detection: A Comprehensive Review	CNN, ViT, Hybrid Models Review	N/A	Comprehensive survey of DL approaches	Data scarcity challenges
[8]	Beena and Sangeetha (2025)	A Customized CNN for Arecanut Disease Detection	Customized CNN	97.33	High disease detection accuracy	Limited disease classes
[9]	Dhanya et al. (2025)	Detection of Tomato Leaf Diseases Using Deep Learning and Spatial Attention Mechanisms	Attention-Based CNN	94–98.9	Enhanced feature extraction	Dataset dependency

[10]	Rezvan et al. (2025)	Automated Rice Seedling Segmentation and Unsupervised Health Assessment Using SAM	SAM + One-Class SVM	94.7 (Dice)	Annotation-free monitoring	Crop-specific validation
[11]	Kumar et al. (2025)	Disease Detection in Areca Nut Using Deep Learning	ResNet18 Transfer Learning	98.12	High accuracy and low inference time	Limited dataset size
[12]	Ashwini et al. (2025)	Deep Learning in Arecanut Research: A Comprehensive Survey	Survey	N/A	Identifies research gaps	No experimental validation
[13]	Muhammad et al. (2025)	A Comprehensive Review of Crop Stress Detection	ML/DL + IoT + UAV Review	N/A	Covers destructive and non-destructive methods	High implementation cost
[14]	Hossen et al. (2025)	Transfer Learning in Agriculture: A Review	Transfer Learning Review	N/A	Effective under limited-data scenarios	Domain adaptation issues
[15]	Patra et al. (2025)	An Explainable Vision Transformer with Transfer Learning Based Efficient Drought Stress Identification	ViT + Transfer Learning	High	Explainable drought detection	Focused on drought stress only
[16]	Vidhya Shree et al. (2024)	Transfer Learning Based Areca Nut Disease Detection Using CNN and SVM Approaches with ResNet50	ResNet50 + SVM	>90	Effective transfer learning	Limited field validation

[17]	Lei et al. (2024)	Deep Learning Implementation of Image Segmentation in Agricultural Applications	U-Net, GAN, Mask R-CNN, Transformers	N/A	Comprehensive segmentation review	Annotation complexity
[18]	Zhang et al. (2024)	The Application of Hyperspectral Imaging for Wheat Biotic and Abiotic Stress Analysis	HSI + ML/DL Review	N/A	Early stress detection	High sensor cost
[19]	Zhang et al. (2024)	Machine Learning Analysis of Maize Seedling Traits Under Drought Stress	XGBoost, Random Forest	AUC ≈ 0.993	Excellent drought prediction	Crop-specific study
[20]	Jones et al. (2024)	Multi-Sensor and Multi-Temporal High-Throughput Phenotyping for Water-Limiting Stress Detection in Soybean	Multi-sensor ML Framework	N/A	Early stress monitoring	Complex data acquisition
[21]	Houetohossou et al. (2023)	Deep Learning Methods for Biotic and Abiotic Stress Detection and Classification in Fruits and Vegetables	Review	N/A	Comprehensive review	Limited focus on plantation crops
[22]	Kushalatha and Prasantha (2023)	Prediction of Arecanut Disease Severity Using Hyperspectral Imaging	LightGBM + HSI	High	Accurate disease severity prediction	Expensive hyperspectral setup

[23]	Balipa et al. (2022)	Arecanut Disease Detection Using CNN and SVM Algorithms	CNN and SVM	CNN: 90, SVM: 75	Simple and effective approach	Small dataset
[24]	Thakur et al. (2022)	Explainable Vision Transformer Enabled CNN for Plant Disease Identification: PlantXViT	CNN + ViT	98.86	Explainable and lightweight model	Requires large training data
[25]	Lei et al. (2021)	Remote Sensing Detection of Yellow Leaf Disease of Arecanut Based on UAV Multisource Sensors	UAV + Remote Sensing	N/A	Large-scale disease monitoring	UAV deployment cost

3.3 Summary of Reviewed Literature

The reviewed studies highlight substantial advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) models for plant stress detection and crop health monitoring. Graph Neural Networks (GNNs), Convolutional Neural Networks (CNNs), transfer learning models, Vision Transformer (ViT)-based architectures have demonstrated strong classification performance in identifying plant diseases and stress conditions [1], [2], [7], [14], [24]. Advanced methods such as multimodal learning, Explainable Artificial Intelligence (XAI), and transformer-based models have further improved model performance, interpretability, and robustness [3], [5], [15], [24].

In addition, hyperspectral imaging, thermal imaging, and UAV-based remote sensing technologies have supported non-destructive, large-scale, and early-stage stress detection, supporting precision agriculture applications [3], [18], [22], [25]. Several review studies have also highlighted the growing importance of AI-driven monitoring systems for sustainable crop management and agricultural decision-making [7], [12], [13], [21].

Despite these improvements, multiple challenges remain unresolved, including limited availability of annotated datasets, environmental variability, computational complexity, model interpretability, and difficulties in real-world deployment [4], [7], [12], [13], [18]. Furthermore, research specifically focused on comprehensive arecanut stress detection encompassing both biotic and abiotic stress conditions remains relatively limited [11], [12]. These limitations reveal important research gaps and highlight the need for more scalable, robust, and explainable stress detection frameworks for sustainable arecanut cultivation.

4. RESEARCH GAP IN THE EXISTING WORK

The research work conducted in recent years has shown promising results in AI, ML and DL-based plant stress detection. However, many limitations still remain, limiting the effectiveness and practical implementation of these approaches in arecanut cultivation. The major research gaps observed in the literature are as follows:

- Most existing studies primarily focus on fungal, bacterial, and viral disease detection, while other important biotic and abiotic stresses, such as pests, nematodes, drought, salinity, nutrient deficiencies, and temperature-related stress conditions, remain underexplored.
- Present approaches are primarily designed for single-stress classification and are unable to effectively detect multiple concurrent stress conditions that frequently occur in real-field environments.

- The availability of large-scale, diverse, and well-annotated arecanut datasets remains limited. Most datasets are collected in real-world conditions but lack adequate variability, limiting model robustness and generalization capability.
- Many proposed methods focus on improving classification accuracy but place insufficient emphasis on processing efficiency, lightweight model architectures, and real-time deployment on mobile, edge, and IoT-enabled agricultural systems.
- Early-stage stress identification and model interpretability remain significant challenges. Majority of DL-based models depend on visible symptoms and operate as black-box systems, limiting trust and practical adoption in agriculture.

5. LINE OF RESEARCH IN FUTURE

The advancement of intelligent arecanut stress detection systems can be carried out through the following steps.

- Detecting the problems in recent arecanut stress detection systems such as reduced accuracy, small datasets, and lack of real-world use.
- Developing a framework that can detect various stresses at the same time, including diseases and environmental problems.
- Creating a large-scale and high-quality dataset of arecanut plants under different conditions using cameras, sensors and drones.
- Building fast and lightweight models for real-time stress detection on mobile and edge devices.
- Using explainable AI methods to make model decisions easier to understand and trust.
- Using advanced learning methods to achieve reliable performance with limited labeled data.
- Merging image data with sensor data such as temperature, soil conditions, and humidity for improved accuracy.
- Comparing the proposed system with current methods to evaluate its performance and effectiveness.

6. CONCLUSION

This survey paper gives a better idea of required attributes to manage arecanut stress detection systems for improving crop productivity, disease management, and sustainable agricultural practices. The study of recent work in Artificial Intelligence techniques, Machine Learning techniques, and Deep Learning techniques such as CNNs, transfer learning models, attention-based architectures, hyperspectral imaging, and UAV-assisted monitoring systems has been reviewed. From the above existing research survey, it is observed that most studies mainly focus on disease detection, while abiotic stresses, multi-stress scenarios, and early-stage stress detection remain less explored. Based on the survey, research gaps such as limited datasets, environmental variability, and real-time deployment issues are identified. Finally, future research ideas for improving automated arecanut stress detection systems are presented.

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