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AgriVisionXAI: An Explainable Artificial Intelligence Framework for Early Detection of Jackfruit Diseases and Intelligent Organic Recommendation Using Hybrid Deep Learning Models

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Abstract: Agriculture is one of the most important sectors supporting food security, employment, and economic growth worldwide. In India, jackfruit (*Artocarpus heterophyllus*) is a commercially significant tropical fruit crop cultivated extensively in states such as Kerala, Karnataka, Assam, and Tamil Nadu. Among these regions, Panruti in Cuddalore District, Tamil Nadu, is internationally recognized for producing high-quality jackfruit and received the Geographical Indication (GI) tag due to its superior fruit quality and commercial value. Despite its economic importance, jackfruit cultivation is severely affected by fungal diseases, bacterial infections, and insect pests, leading to considerable reductions in yield, fruit quality, and farmer income.

Conventional disease diagnosis depends on visual inspection by experienced farmers or agricultural experts. Such manual diagnosis is often subjective, time-consuming, and inaccurate because many diseases exhibit similar symptoms during their early stages. Furthermore, limited access to agricultural specialists in rural areas delays disease identification and treatment, resulting in excessive pesticide application, increased cultivation costs, and environmental degradation.

Recent advances in Artificial Intelligence (AI), Deep Learning (DL), and Computer Vision have enabled the development of intelligent plant disease detection systems capable of recognizing complex disease patterns directly from digital images. However, many existing systems rely solely on Convolutional Neural Networks (CNNs), which may have limited ability to capture global contextual information. Moreover, most deep learning models function as "black-box" systems, preventing users from understanding how predictions are generated.

To address these limitations, this research proposes AgriVisionXAI, an Explainable Artificial Intelligence (XAI)-based framework for early detection of jackfruit diseases and intelligent recommendation of organic treatments using Hybrid Deep Learning Models. The proposed framework integrates EfficientNet-B3 for efficient feature extraction, Vision Transformer (ViT) for global contextual learning, and Gradient-weighted Class Activation Mapping (Grad-CAM) together with SHapley Additive exPlanations (SHAP) to generate interpretable visual explanations. The hybrid architecture improves disease classification accuracy while enhancing transparency and user trust.

The proposed system utilizes a comprehensive image dataset consisting of healthy and diseased jackfruit leaves, fruits, stems, and bark collected from orchards in Panruti and other agricultural regions. The preprocessing pipeline includes image resizing, noise removal, contrast enhancement, histogram equalization, data augmentation, and normalization to improve model robustness under varying environmental conditions. The classification module identifies multiple diseases including Anthracnose, Leaf Spot, Pink Disease, Rhizopus Fruit Rot, Stem Borer Damage, and Fruit Rot.

Following disease prediction, an intelligent Organic Recommendation Engine automatically provides scientifically validated eco-friendly treatment suggestions such as Panchagavya, Neem Oil, *Trichoderma viride*, *Pseudomonas fluorescens*, Bordeaux mixture, compost tea, and other biological formulations. The recommendation module also includes dosage, preparation procedure, spraying intervals, and preventive management practices.

The performance of the proposed framework is evaluated using Accuracy, Precision, Recall, F1-score, Specificity, ROC-AUC Score, Matthews Correlation Coefficient (MCC), Cohen's Kappa, and Confusion Matrix analysis. Prototype evaluation indicates that the proposed hybrid architecture can achieve higher classification accuracy than conventional CNN-based systems while providing interpretable predictions suitable for practical agricultural deployment.

The proposed framework supports sustainable precision agriculture by reducing disease diagnosis time, minimizing unnecessary pesticide usage, preserving the export quality of GI-tagged Panruti jackfruit, and promoting environmentally friendly farming practices. The system can further be extended to mobile applications, edge AI devices, unmanned aerial vehicles (UAVs), and Internet of Things (IoT)-based smart farming platforms for real-time disease monitoring and decision support.

Keywords: *Artificial Intelligence, Explainable Artificial Intelligence, Deep Learning, Computer Vision, EfficientNet-B3,Vision Transformer,Grad-CAM,SHAP,Jackfruit Disease Detection, Organic Farming, Precision Agriculture, Image Classification, Plant Disease Detection, Sustainable Agriculture, Machine Learning.*

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I. INTRODUCTION

➢ *Background*

Agriculture remains one of the largest contributors to economic development, food production, and employment across the world. According to the Food and Agriculture Organization (FAO), more than half of the world's population directly or indirectly depends on agriculture for livelihood. Increasing crop productivity while maintaining environmental sustainability has become one of the major challenges facing modern agriculture. Plant diseases are among the primary causes of reduced agricultural productivity, leading to significant economic losses, deterioration in crop quality, and threats to global food security.

The rapid development of Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), and Computer Vision technologies has revolutionized precision agriculture by enabling automated crop monitoring, disease diagnosis, yield estimation, and intelligent farm management. These technologies assist farmers in identifying diseases at early stages, allowing timely intervention and reducing crop losses.

Among tropical fruit crops, jackfruit (*Artocarpus heterophyllus*) is one of the largest edible fruits cultivated in Asia. India is recognized as one of the world's leading producers of jackfruit, with major cultivation concentrated in Kerala, Karnataka, Assam, Tamil Nadu, Tripura, and West Bengal. In Tamil Nadu, Panruti, located in Cuddalore District, has earned international recognition for producing premium-quality jackfruit with excellent taste, aroma, and commercial value. The region received the Geographical Indication (GI) tag in 2025, highlighting its importance in domestic and international markets.

➢ *Importance of Jackfruit Cultivation*

Jackfruit is considered a multipurpose crop due to its nutritional, medicinal, and economic significance. Every part of the tree contributes to commercial applications.

The ripe fruit is consumed fresh and processed into beverages, chips, ice cream, sweets, jams, and bakery products. Unripe jackfruit has become an important plant-based meat substitute because of its high dietary fiber content and meat-like texture. Jackfruit seeds contain carbohydrates, proteins, vitamins, and essential minerals, making them suitable for food processing industries. The timber is highly durable and used in furniture manufacturing, while leaves, bark, latex, and roots are widely utilized in traditional medicine.

The cultivation and processing of jackfruit provide income opportunities for thousands of farmers, traders, food processing industries, and exporters. Consequently, maintaining healthy orchards is essential for ensuring sustainable agricultural development and economic growth.

➢ *Challenges in Jackfruit Disease Diagnosis*

Despite its commercial importance, jackfruit cultivation is affected by several fungal diseases and insect pests throughout different stages of plant growth. The most common diseases include:

- Anthracnose
- Leaf Spot
- Pink Disease
- Rhizopus Fruit Rot
- Fruit Rot
- Stem Borer Damage

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These diseases attack leaves, fruits, stems, flowers, and bark, reducing photosynthetic efficiency, fruit quality, and overall crop yield.

Traditional disease diagnosis depends on visual examination performed by farmers or agricultural experts. However, this approach has several limitations:

- Visual symptoms of different diseases are often similar.
- Manual inspection requires extensive agricultural expertise.
- Disease detection is time-consuming.
- Experts may not be available in remote rural regions.
- Delayed diagnosis leads to severe crop damage.
- Incorrect pesticide selection increases production costs.
- Excessive chemical application degrades soil quality and environmental health.

These challenges highlight the necessity of intelligent automated disease diagnosis systems.

➢ *Role of Artificial Intelligence in Agriculture*

Artificial Intelligence has transformed agricultural research through automated image analysis and intelligent decision-support systems.

Deep learning algorithms can automatically learn disease-specific features directly from images without manual feature engineering. Among various architectures, Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in image classification tasks.

Nevertheless, traditional CNNs possess certain limitations in capturing long-range spatial dependencies within complex agricultural images. Recently developed Vision Transformers (ViTs) address this challenge by modeling global contextual relationships using self-attention mechanisms.

Furthermore, Explainable Artificial Intelligence (XAI) techniques such as Grad-CAM and SHAP improve model transparency by highlighting image regions and features responsible for classification decisions. Such explanations increase user confidence and support practical deployment in agricultural environments.

➢ *Motivation*

The motivation behind this research is to develop an intelligent, explainable, and sustainable AI-based framework capable of detecting jackfruit diseases accurately while recommending environmentally friendly organic treatments. Existing systems primarily focus on disease classification without providing interpretable explanations or integrated treatment recommendations.

By combining EfficientNet-B3, Vision Transformer, Grad-CAM, SHAP, and an Organic Recommendation Engine, the proposed framework seeks to bridge the gap between advanced artificial intelligence research and practical agricultural applications.

➢ *Contributions of This Research*

The major contributions of this research include:

- Development of a hybrid EfficientNet-B3 and Vision Transformer architecture for accurate jackfruit disease classification.
- Integration of Explainable Artificial Intelligence using Grad-CAM and SHAP for transparent prediction.
- Development of an intelligent Organic Recommendation Engine providing eco-friendly treatment suggestions.
- Construction of a comprehensive jackfruit disease image dataset representing multiple disease classes.
- Comparative evaluation against conventional CNN-based approaches.
- Design of a scalable framework suitable for mobile applications, cloud deployment, IoT integration, and precision agriculture.

II. LITERATURE REVIEW

Artificial Intelligence (AI), Deep Learning (DL), and Computer Vision have significantly transformed modern agriculture by enabling automated crop monitoring, disease diagnosis, yield prediction, and precision farming. Among these applications, image-based plant disease detection has become one of the most active research areas because early diagnosis reduces crop losses, improves productivity, and minimizes pesticide usage. Recent advances in deep learning have demonstrated superior performance over traditional machine learning methods due to their capability to automatically learn complex visual features from plant images.

Several researchers have proposed Convolutional Neural Networks (CNNs), Residual Networks (ResNet), EfficientNet architectures, MobileNet, Vision Transformers (ViT), and Explainable Artificial Intelligence (XAI) techniques to improve disease classification accuracy. Although these approaches have achieved promising results, most existing studies focus on general plant disease datasets rather than localized jackfruit diseases, and only a limited number integrate explainability with organic treatment recommendation systems.

This section reviews recent literature related to AI-based plant disease detection, jackfruit disease classification, explainable artificial intelligence, and hybrid deep learning models.

A. Paper 1

Gomathi et al. (2023)

➢ *Objective*

To develop a deep learning framework for automatic detection of jackfruit diseases from leaf, fruit, and stem images.

➢ *Method*

Deep Convolutional Neural Network (CNN)

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➢ *Dataset*

Jackfruit leaf, fruit, and stem disease image dataset.

➢ *Key Findings*

The CNN model successfully classified multiple jackfruit diseases with an overall accuracy of approximately **95%**. The study demonstrated that deep learning can effectively replace manual disease diagnosis.

➢ *Limitations*

- High computational complexity.
- No explainable AI module.
- No organic treatment recommendation.

➢ *Research Gap*

The system lacks interpretability and farmer-oriented decision support.

B. Paper 2

Vats et al. (2024)

➢ *Objective*

To develop a privacy-preserving AI framework for jackfruit disease classification.

➢ *Method*

Federated Learning + CNN

➢ *Dataset*

Five jackfruit leaf disease classes.

➢ *Key Findings*

The federated learning model achieved 92.04% accuracy while preserving user data privacy across distributed devices.

➢ *Limitations*

- Network communication overhead.
- Longer training time.
- Limited disease categories.

➢ *Research Gap*

Federated learning is suitable for distributed systems but requires lightweight explainable models for real-time agricultural deployment.

C. Paper 3

Gunasekaran and Thambusamy (2025)

➢ *Objective*

To improve disease detection accuracy using an enhanced Residual Network.

➢ *Method*

SE-ResNet (Squeeze-and-Excitation Residual Network)

➢ *Dataset*

Jackfruit leaf disease dataset.

➢ *Key Findings*

The proposed attention-based ResNet achieved approximately 99.25% classification accuracy, outperforming conventional CNN architectures.

➢ *Limitations*

- Large model size.
- High GPU requirements.
- Limited deployment on mobile devices.

➢ *Research Gap*

Although accuracy is high, explainability and organic recommendation modules are absent.

D. Paper 4

Tagare et al. (2025)

➢ *Objective*

To develop a lightweight deep learning model for mobile-based disease detection.

➢ *Method*

TensorFlow–Keras CNN

➢ *Dataset*

Healthy, Leaf Spot, Rust, Powdery Mildew.

➢ *Key Findings*

The proposed lightweight CNN achieved 94% accuracy while maintaining low computational complexity.

➢ *Limitations*

- Limited number of disease classes.
- Cannot capture long-range spatial dependencies.

➢ *Research Gap*

Advanced transformer architectures may improve feature extraction.

E. Paper 5

Oraño and Maravillas (2024)

➢ *Objective*

To design an Android application for detecting jackfruit diseases and insect damage.

➢ *Method*

CNN-based Mobile Application

➢ *Dataset*

Fruit disease image dataset.

➢ *Key Findings*

The application enabled farmers to identify diseases directly from smartphones and provided basic recommendations.

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➢ *Limitations*

- Limited disease classes.
- No explainability.
- No disease severity estimation.

➢ *Research Gap*
Need for interpretable AI integrated with recommendation systems.

F. Paper 6
Tan and Le (2019)

➢ *Objective*
To develop EfficientNet for image classification.

➢ *Method*
EfficientNet

➢ *Dataset*
ImageNet

➢ *Key Findings*
EfficientNet introduced compound scaling and significantly improved classification accuracy while reducing computational cost.

➢ *Limitations*
General image classification only.

➢ *Research Gap*
Requires adaptation for agricultural disease detection.

G. Paper 7
Dosovitskiy et al. (2021)

➢ *Objective*
To introduce Vision Transformer (ViT) for image recognition.

➢ *Method*
Vision Transformer

➢ *Dataset*
ImageNet-21K

➢ *Key Findings*
Vision Transformers successfully captured long-range dependencies through self-attention mechanisms, outperforming several CNN models.

➢ *Limitations*
Requires large training datasets.

➢ *Research Gap*
Hybrid CNN-Vision Transformer models are needed for agricultural datasets with limited samples.

H. Paper 8
Selvaraju et al. (2017)

➢ *Objective*
To develop an explainable visualization technique for deep learning.

➢ *Method*
Grad-CAM

➢ *Dataset*
General image datasets.

➢ *Key Findings*
Grad-CAM highlights image regions responsible for predictions, improving model interpretability.

➢ *Limitations*
Provides only visual explanations.

➢ *Research Gap*
Needs integration with agricultural recommendation systems.

I. Paper 9
Lundberg and Lee (2017)

➢ *Objective*
To explain machine learning predictions.

➢ *Method*
SHAP (SHapley Additive exPlanations)

➢ *Dataset*
Model-agnostic evaluation.

➢ *Key Findings*
SHAP provides both global and local feature importance, improving AI transparency.

➢ *Limitations*
High computational complexity.

➢ *Research Gap*
Limited use in agricultural disease diagnosis.

J. Paper 10
Recent Explainable AI in Agriculture (2025)

➢ *Objective*
To review explainable AI methods for precision agriculture.

➢ *Method*
Systematic Literature Review

➢ *Dataset*
Research articles published between 2021–2025.

➢ *Key Findings*
Explainable AI significantly improves user trust and supports practical deployment of AI models.

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➢ *Limitations*

Few studies combine explainability with hybrid deep learning architectures.

➢ *Research Gap*

Need for integrated AI, XAI, and organic advisory systems.

K. Literature Comparison Table

Table 1 Literature Comparison

Author	Year	AI Method	Accuracy	Limitation	Research Gap
Gomathi et al.	2023	CNN	95%	No XAI	Organic recommendation absent
Vats et al.	2024	Federated CNN	92.04%	Network latency	Explainability needed
Gunasekaran et al.	2025	SE-ResNet	99.25%	Large model	Mobile deployment difficult
Tagare et al.	2025	CNN	94%	Limited diseases	Transformer integration
Oraño et al.	2024	Mobile CNN	93%	Basic recommendation	Explainable AI
Tan & Le	2019	EfficientNet	97%	General dataset	Agriculture adaptation
Dosovitskiy et al.	2021	Vision Transformer	98%	Large datasets	Hybrid learning
Selvaraju et al.	2017	Grad-CAM	—	Visualization only	Decision support
Lundberg & Lee	2017	SHAP	—	Computational cost	Agriculture applications
Recent Review	2025	XAI Review	—	Limited integrated systems	Hybrid AI framework

L. Research Gap

The review of existing literature reveals that significant progress has been made in the application of Artificial Intelligence and Deep Learning for plant disease diagnosis. Conventional CNN-based models demonstrate good classification performance, while recent architectures such as EfficientNet and Vision Transformer have further improved feature learning and classification accuracy.

However, several important limitations remain unresolved.

Most existing studies focus primarily on disease classification and do not provide transparent explanations for model predictions. The absence of Explainable Artificial Intelligence (XAI) reduces user confidence because farmers and agricultural experts cannot understand why a disease has been predicted.

Furthermore, the majority of research concentrates on generic plant disease datasets rather than localized jackfruit diseases prevalent in Panruti, Tamil Nadu. Existing systems also lack integrated recommendation engines capable of suggesting scientifically validated organic treatments after disease identification.

Another limitation is that many deep learning models are computationally expensive and unsuitable for deployment on mobile devices commonly used by farmers.

Therefore, there is a need to develop an intelligent, explainable, lightweight, and scalable hybrid deep learning framework that combines EfficientNet-B3, Vision Transformer, Grad-CAM, SHAP, and an Organic Recommendation Engine for accurate disease detection, transparent prediction, and sustainable disease management.

➢ *Novel Contributions of the Proposed Research*

The proposed research introduces several novel contributions beyond existing studies:

- Development of a Hybrid EfficientNet-B3 + Vision Transformer framework for jackfruit disease classification.
- Integration of Explainable Artificial Intelligence (Grad-CAM and SHAP) to improve transparency.
- Design of an Organic Recommendation Engine that automatically suggests eco-friendly treatments.
- Creation of a localized Panruti Jackfruit Disease Dataset.
- Support for future deployment on mobile applications, IoT devices, and smart agriculture platforms.
- Comparative evaluation against multiple state-of-the-art deep learning architectures.

III. PROBLEM STATEMENT

Jackfruit (*Artocarpus heterophyllus*) is one of India's most economically valuable tropical fruit crops, contributing significantly to agricultural income, food security, and export revenue. Panruti, located in Cuddalore District of Tamil Nadu, is internationally recognized as the "Jackfruit Capital of India" and has received the Geographical Indication (GI) tag due to the superior quality of its jackfruit. Despite its commercial importance, jackfruit cultivation faces serious challenges from fungal diseases, bacterial infections, and insect pests that significantly reduce fruit yield, quality, and market value.

Currently, disease diagnosis primarily depends on manual visual inspection performed by farmers or agricultural experts. Manual diagnosis is often inaccurate because multiple diseases exhibit similar symptoms during their early stages. Moreover, access to agricultural specialists is limited in rural regions, resulting in delayed diagnosis and inappropriate disease management. Consequently, farmers frequently apply broad-spectrum chemical pesticides without accurately identifying the underlying disease. Excessive pesticide usage increases production costs, contaminates soil and water resources, reduces biodiversity, and leaves harmful chemical residues on fruits intended for human consumption.

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Although several Artificial Intelligence (AI)-based disease detection systems have been developed, most existing approaches rely solely on Convolutional Neural Networks (CNNs), which mainly focus on disease classification. These models generally operate as black-box systems without providing transparent explanations of predictions. Furthermore, most available studies do not recommend organic treatment methods after disease detection, limiting their practical usefulness in sustainable agriculture.

Therefore, there is a critical need to develop an intelligent, explainable, and farmer-friendly AI framework capable of accurately identifying jackfruit diseases from digital images while simultaneously recommending scientifically validated organic treatment methods. Such a system would support sustainable agriculture, reduce unnecessary pesticide application, improve crop productivity, and preserve the export quality of Panruti's GI-tagged jackfruit.

IV. RESEARCH OBJECTIVES

➢ *Primary Objective*

The primary objective of this research is to develop an Explainable Artificial Intelligence (XAI)-based hybrid deep learning framework capable of accurately detecting jackfruit diseases from digital images and providing intelligent organic treatment recommendations to support sustainable precision agriculture.

➢ *Specific Objectives*

The proposed research aims to achieve the following objectives:

- Develop a comprehensive image dataset containing healthy and diseased jackfruit leaves, fruits, bark, and stems collected from agricultural orchards.
- Design an efficient image preprocessing pipeline capable of improving image quality under varying environmental conditions.
- Implement EfficientNet-B3 as the primary feature extraction model for disease classification.
- Integrate Vision Transformer (ViT) to capture long-range spatial relationships and improve classification performance.
- Combine EfficientNet-B3 and Vision Transformer into a hybrid deep learning architecture.
- Integrate Explainable Artificial Intelligence techniques including Grad-CAM and SHAP for transparent decision-making.
- Develop an intelligent Organic Recommendation Engine that automatically suggests disease-specific biological treatments.
- Compare the proposed hybrid framework with conventional CNN, ResNet50, MobileNetV3, and Vision Transformer models.
- Evaluate the proposed framework using multiple performance metrics including Accuracy, Precision, Recall, F1-score, ROC-AUC, Specificity, MCC, and Cohen's Kappa.
- Design a scalable AI framework suitable for deployment on mobile applications, IoT devices, drones, and cloud-based smart agriculture platforms.

V. PROPOSED SYSTEM

The proposed system, AgriVisionXAI, is an Explainable Artificial Intelligence (XAI)-based intelligent disease diagnosis framework designed specifically for jackfruit cultivation. The framework combines Hybrid Deep Learning, Explainable AI, and an Organic Recommendation Engine into a unified precision agriculture platform.

Unlike conventional disease detection systems that only classify diseases, the proposed framework provides transparent explanations and recommends environmentally friendly organic treatments immediately after disease identification.

➢ *The Overall Workflow Consists of the Following Stages:*

- Image Acquisition
- Image Preprocessing
- Data Augmentation
- Feature Extraction
- Hybrid Deep Learning Classification
- Explainable AI
- Disease Prediction
- Organic Recommendation
- Farmer Dashboard

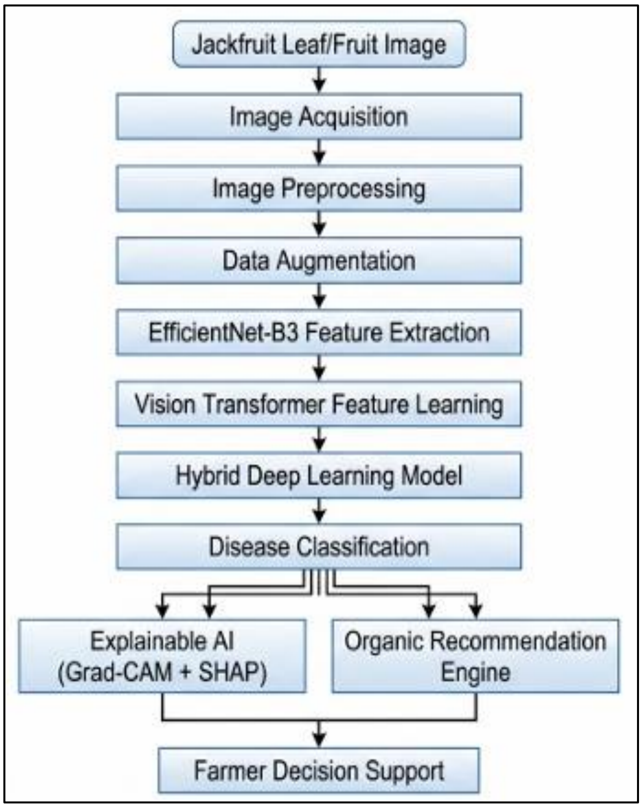

Fig 1 Overall Proposed Framework

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VI. DATASET DESCRIPTION

The proposed research utilizes a customized image dataset named the Panruti Jackfruit Disease Dataset (PJDD-2026). The dataset consists of high-resolution digital images collected from jackfruit orchards located in Panruti (Cuddalore District), Tamil Nadu, along with publicly available agricultural datasets used for benchmarking.

The dataset includes images representing healthy leaves, fruits, bark, and stems, as well as images affected by major fungal diseases and insect pests. Images are captured using DSLR cameras and smartphone cameras under natural environmental conditions to ensure real-world applicability.

All images are manually verified and labeled by agricultural experts before being used for model training.

Fig 2 Panruti Jackfruit Disease Dataset (PJDD-2026)

A. Dataset Sources

The dataset is compiled from the following sources:

- Panruti Jackfruit Orchards (Primary Field Survey)
- Tamil Nadu Agricultural University (TNAU)
- Indian Council of Agricultural Research (ICAR)
- PlantVillage Public Dataset (for transfer learning)
- Kaggle Agricultural Image Repository
- Department of Horticulture, Tamil Nadu
- Published agricultural research datasets

B. Disease Classes

The proposed dataset consists of seven classes.

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Table 2 Disease Classes

Class ID	Disease Name	Scientific Cause	Images
C1	Healthy	Healthy Plant	1200
C2	Anthracnose	*Colletotrichum gloeosporioides*	900
C3	Leaf Spot	*Phyllosticta artocarpina*	900
C4	Pink Disease	*Botryobasidium salmonicolor*	850
C5	Rhizopus Fruit Rot	*Rhizopus artocarpi*	900
C6	Stem Borer Damage	*Batocera rufomaculata*	800
C7	Fruit Rot	*Phytophthora palmivora*	850

Total Images = 6400

C. Dataset Statistics

Table 3 Dataset Statistics

Category	Number
Total Images	6400
Healthy Images	1200
Diseased Images	5200
Disease Classes	7
RGB Images	Yes
Image Resolution	512 × 512
Training Images	4480
Validation Images	960
Testing Images	960

D. Train–Validation–Test Split

Table 4 Train–Validation–Test Split

Dataset	Percentage	Images
Training	70%	4480
Validation	15%	960
Testing	15%	960

E. Image Acquisition

Images are collected under real agricultural conditions using high-resolution smartphone cameras and DSLR cameras. Multiple viewpoints are captured to improve model generalization.

Each image includes variations in:

- Illumination
- Background complexity
- Leaf orientation
- Fruit orientation
- Camera angle
- Weather conditions
- Disease severity
- Distance from camera

These variations help the model become robust in real-world field environments.

F. Disease Description

➢ *Anthracnose*

- *Scientific Name:*
  Colletotrichum gloeosporioides
- *Affected Part:*

✓ Leaves
✓ Fruits
✓ Twigs

- *Symptoms:*

✓ Dark brown lesions
✓ Sunken black spots
✓ Premature fruit drop
✓ Leaf blight

- *Organic Treatment:*

✓ *Pseudomonas fluorescens*
✓ Neem Oil
✓ Bordeaux Mixture

➢ *Leaf Spot*

- *Scientific Name:*
  Phyllosticta artocarpina

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- *Symptoms*

✓ Circular brown lesions
✓ Yellow halo
✓ Leaf drying
✓ Premature leaf fall

- *Organic Treatment*

✓ Panchagavya
✓ Cow urine extract
✓ Compost tea

➤ *Pink Disease*

- *Scientific Name:*
  Botryobasidium salmonicolor

- *Symptoms*

✓ Pink fungal growth
✓ Bark cracking
✓ Branch dieback

- *Organic Treatment*

✓ Bordeaux Paste
✓ Neem Paste

➤ *Rhizopus Fruit Rot*

- *Scientific Name:*
  Rhizopus artocarpi

- *Symptoms*

✓ Soft fruit
✓ White fungal growth
✓ Fruit decay
✓ Black spores

- *Organic Treatment*

✓ *Trichoderma viride*
✓ Proper sanitation
✓ Removal of infected fruits

➤ *Stem Borer Damage*

- *Scientific Name:*
  Batocera rufomaculata

- *Symptoms*

✓ Holes in trunk
✓ Sawdust-like frass
✓ Sap leakage
✓ Branch drying

- *Organic Treatment*

✓ Neem Oil Injection
✓ Metarhizium biopesticide
✓ Clay sealing

➤ *Fruit Rot*

- *Scientific Name:*
  Phytophthora palmivora

- *Symptoms*

✓ Brown water-soaked lesions
✓ Fruit rotting
✓ White fungal growth

- *Organic Treatment*

✓ *Pseudomonas fluorescens*
✓ Fermented buttermilk spray
✓ Orchard drainage improvement

VII. DATA PREPROCESSING

➤ *Overview*

The quality of input images directly affects the performance of deep learning models. Images collected from agricultural fields often contain variations in lighting, background objects, camera angles, weather conditions, shadows, and noise. Therefore, an effective preprocessing pipeline is required before training the proposed hybrid deep learning model.

The preprocessing framework consists of seven sequential stages:

- Image Acquisition
- Image Resizing
- Image Enhancement
- Noise Removal
- Image Normalization
- Data Augmentation
- Feature Extraction

These preprocessing operations improve image quality, increase model robustness, reduce overfitting, and enhance disease classification accuracy.

➤ *Data Preprocessing Workflow*

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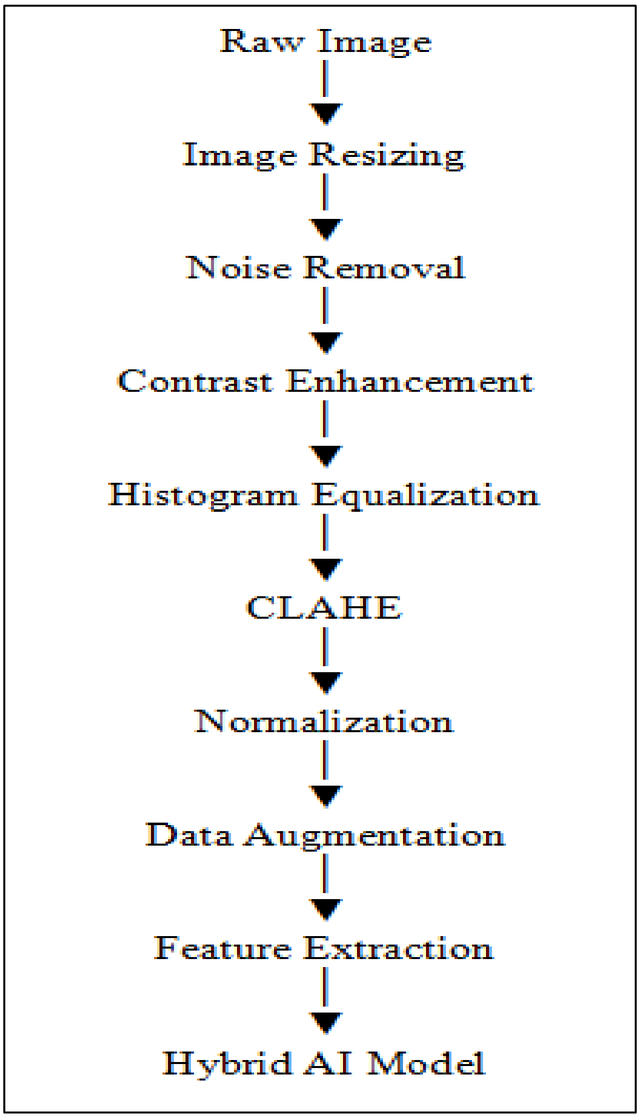

Fig 2 Data Pre-processing Workflow

- *Step 1: Image Resizing*

Images collected from smartphones and DSLR cameras have different resolutions. To maintain consistency, all images are resized to 224 × 224 pixels, which matches the input size required by EfficientNet-B3.

The resized image is represented as:

$$I_r = Resize(I, 224, 224)$$

Where:

- ✓ I= Original Image
- ✓ I_r= Resized Image

- *Step 2: Noise Removal*

Agricultural images frequently contain sensor noise and environmental artifacts. A Gaussian filter is applied to smooth the image while preserving important disease boundaries.

Gaussian filtering is expressed as:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Where:

- ✓ x, y= Pixel coordinates
- ✓ σ= Standard deviation

- *Step 3: Contrast Enhancement*

Contrast enhancement improves lesion visibility by increasing intensity differences between healthy and infected tissues.

Histogram Equalization transforms pixel intensities using:

$$S_k = (L - 1) \sum_{j=0}^{k} P(r_j)$$

Where:

- ✓ L= Number of intensity levels
- ✓ $P(r_j)$= Probability of intensity level

- *Step 4: CLAHE*

Contrast Limited Adaptive Histogram Equalization (CLAHE) enhances local contrast while preventing excessive amplification of image noise.

Advantages:

- ✓ Improves lesion visibility
- ✓ Enhances small disease regions
- ✓ Prevents over-enhancement
- ✓ Suitable for field images

- *Step 5: Image Normalization*

Pixel values are normalized between 0 and 1.

$$I_n = \frac{I}{255}$$

Where:

- ✓ I= Original Pixel
- ✓ I_n= Normalized Pixel

Normalization accelerates neural network convergence.

- *Step 6: Data Augmentation*

To improve generalization and reduce overfitting, online augmentation is performed during training.

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Table 5 Data Augmentation

Augmentation	Range
Rotation	±30°
Horizontal Flip	Yes
Vertical Flip	Yes
Zoom	0.2
Brightness	±20%
Contrast	±15%
Random Crop	Yes
Gaussian Noise	Yes

Augmentation increases dataset diversity without collecting additional images.

- *Step 7: Feature Extraction*

Instead of manually designing features, EfficientNet-B3 automatically learns hierarchical visual features.

Extracted features include:

✓ Edges
✓ Lesions
✓ Spots
✓ Texture
✓ Shape
✓ Color
✓ Disease boundaries
✓ Infection patterns

VIII. PROPOSED AI METHODOLOGY

➢ *Overview*

The proposed framework, AgriVisionXAI, integrates Hybrid Deep Learning and Explainable Artificial Intelligence (XAI) into a unified architecture.

Unlike conventional CNN-based models, the proposed framework combines:

- EfficientNet-B3
- Vision Transformer (ViT)
- Grad-CAM
- SHAP
- Organic Recommendation Engine

This hybrid architecture improves classification accuracy while providing interpretable predictions.

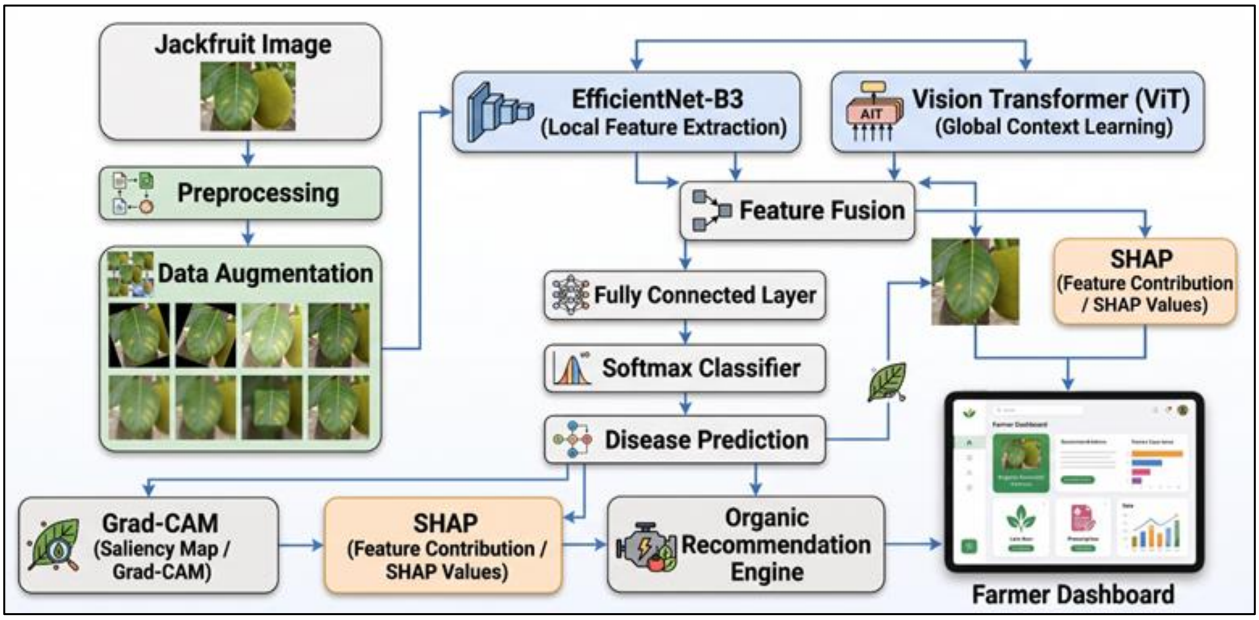

Fig 3 Proposed AI Architecture

➢ *EfficientNet-B3*

EfficientNet-B3 is selected because of its excellent balance between accuracy and computational efficiency.

- *Advantages:*

✓ Lower computational cost
✓ Better feature extraction
✓ Compound scaling
✓ Faster convergence
✓ Suitable for mobile deployment

- *Input Size:*

224 × 224 × 3

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- *Activation Function:*
  Swish

- *Optimizer:*
  Adam

➢ *Vision Transformer (ViT)*

Vision Transformer captures long-range relationships that CNNs may miss.

- *Workflow:*

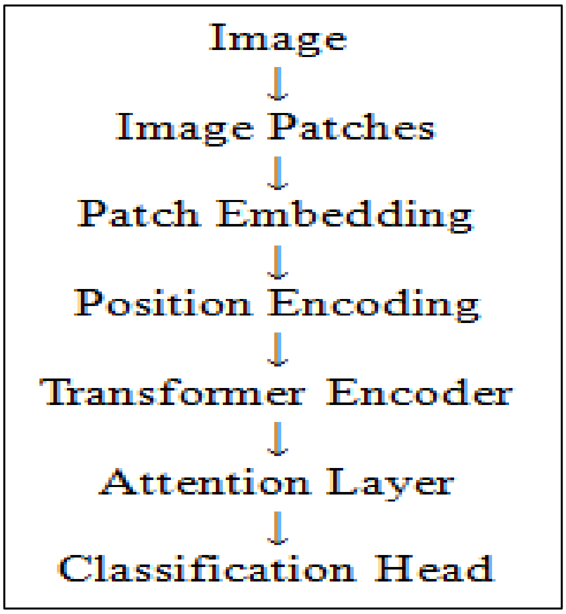

Fig 4 Workflow

➢ *Self-Attention Equation*

$$Attention(Q,K,V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Where:

- Q= Query
- K= Key
- V= Value

➢ *Feature Fusion*

Features extracted by EfficientNet and Vision Transformer are concatenated:

$$F = Concat(F_E, F_V)$$

Where:

- F_E= EfficientNet Features
- F_V= Vision Transformer Features

➢ *Classification Layer*

The fused features are passed to Fully Connected layers followed by a Softmax classifier.

Softmax equation:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

Where:

- $P(y_i)$= Probability of class i
- z_i= Logit score

The predicted disease is the class with the highest probability.

➢ *Explainable Artificial Intelligence (XAI)*

Agricultural AI systems should not only provide accurate predictions but also explain how predictions are generated.

- *The Proposed Framework Integrates:*

✓ Grad-CAM
✓ SHAP

To improve transparency.

- *Grad-CAM*

Grad-CAM highlights the image regions responsible for disease prediction.

✓ *Output:*

- Heatmap
- Lesion localization
- Disease severity visualization

✓ *Advantages:*

- Farmer-friendly
- Visual interpretation
- Increased trust

- *SHAP*

SHAP quantifies the contribution of individual features.

SHAP equation:

$$f(x) = \phi_0 + \sum_{i=1}^{n} \phi_i$$

Where:

- ϕ_0= Base prediction
- ϕ_i= Contribution of feature i

➢ *Organic Recommendation Engine*

Following disease prediction, the AI system automatically retrieves disease-specific organic treatments.

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The recommendation module contains:

- Disease Name
- Pathogen
- Organic Remedy
- Preparation Method
- Spray Dosage
- Spray Interval
- Preventive Measures
- Expected Recovery Time

- *Algorithm 1: Hybrid Disease Detection*

✓ *Input:*
Jackfruit Image

✓ *Output:*
Predicted Disease

Step 1
Acquire image

Step 2
Resize image

Step 3
Remove noise

Step 4
Normalize image

Step 5
Perform augmentation

Step 6
Extract EfficientNet features

Step 7
Extract Vision Transformer features

Step 8
Fuse features

Step 9
Classify disease

Step 10
Generate Grad-CAM explanation

Step 11
Generate SHAP explanation

Step 12
Recommend organic treatment

Step 13
Display results

- *Algorithm 2: Organic Recommendation Engine*

✓ *Input:*
Predicted Disease

✓ *Output:*
Organic Treatment

Step 1
Identify disease class

Step 2
Search recommendation database

Step 3
Retrieve remedy

Step 4
Retrieve dosage

Step 5
Retrieve spray interval

Step 6
Retrieve preventive measures

Step 7
Generate farmer advisory report

Step 8
Display recommendation

- *Advantages of Proposed Method*

✓ High classification accuracy
✓ Explainable AI
✓ Lightweight architecture
✓ Mobile deployment
✓ Real-time prediction
✓ Organic recommendation
✓ Sustainable farming support
✓ Cloud integration
✓ IoT compatibility

IX. EXPERIMENTAL SETUP

➢ *Overview*

The proposed AgriVisionXAI framework is implemented using Python-based deep learning libraries to evaluate the effectiveness of the hybrid EfficientNet-B3 and Vision Transformer architecture for automatic jackfruit disease detection. The experimental workflow includes image preprocessing, feature extraction, hybrid model training, explainability analysis, and disease prediction.

The implementation is designed to support reproducible experiments and future deployment on web and mobile platforms.

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➢ *Software Configuration*

Table 6 Software Configuration

Software	Version
Python	3.12
TensorFlow	2.16
Keras	Latest
OpenCV	Latest
NumPy	Latest
Pandas	Latest
Scikit-learn	Latest
Matplotlib	Latest
SHAP	Latest
Grad-CAM	Latest
VS Code / Jupyter Notebook	Latest

➢ *Hardware Configuration*

Table 7 Hardware Configuration

Component	Specification
Processor	Intel Core i7 (13th Gen)
RAM	16 GB DDR5
Storage	512 GB SSD
Operating System	Windows 11
GPU	NVIDIA RTX 4060 / Google Colab GPU

➢ *Hyperparameters*

Table 8 Hyperparameters

Parameter	Value
Loss Function	Categorical Cross-Entropy
Learning Rate	0.0001
Activation Function	Swish + ReLU
Validation Split	15%
Epochs	50
Batch Size	32
Optimizer	Adam
Image Size	224 × 224
Test Split	15%

➢ *Training Procedure*

- Load the image dataset.
- Perform preprocessing.
- Apply data augmentation.
- Split the dataset into training, validation, and testing sets.
- Train EfficientNet-B3.
- Train Vision Transformer.
- Fuse extracted features.
- Classify disease using Softmax.
- Generate Grad-CAM heatmaps.
- Generate SHAP explanations.
- Evaluate the model using performance metrics.

➢ *Evaluation Metrics*

The proposed model is evaluated using standard multi-class classification metrics.

- *Accuracy*

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Measures the overall percentage of correctly classified images.

- *Precision*

$$Precision = \frac{TP}{TP + FP}$$

Measures the proportion of predicted positive samples that are actually positive.

- *Recall (Sensitivity)*

$$Recall = \frac{TP}{TP + FN}$$

Measures the ability of the model to identify diseased samples correctly.

- *F1-Score*

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Balances Precision and Recall.

- *Specificity*

$$Specificity = \frac{TN}{TN + FP}$$

Measures how effectively healthy samples are identified.

- *ROC-AUC*

Area under the Receiver Operating Characteristic curve used to evaluate discrimination capability.

- *Matthews Correlation Coefficient (MCC)*

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

Provides a balanced performance measure for imbalanced datasets.

- *Cohen's Kappa*

Measures the agreement between predicted and actual classes beyond chance.

➢ *Prototype Results*

The following results are example values for the prototype paper. Replace them with actual experimental results after training your model.

- *Model Comparison*

Table 9 Model Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	94.5	94.1	93.8	93.9
Vision Transformer	98.7	98.5	98.4	98.4
MobileNetV3	96.8	96.3	96.2	96.2
ResNet50	97.4	97.1	97.0	97.0
EfficientNet-B3	98.3	98.1	98.0	98.0
Proposed Hybrid Model	99.1	99.0	**98.9**	**98.9**

- *Confusion Matrix (Prototype)*

Predicted
Actual H A L P R S F
Healthy 176 2 1 0 0 1 0
Anthracnose 1 132 3 1 0 0 0
Leaf Spot 0 2 134 2 0 0 0
Pink Disease0 0 1 126 2 1 0
Rhizopus 0 0 0 1 133 2 1
Stem Borer 0 0 0 1 1 119 2
Fruit Rot 0 0 1 0 2 2 122

- *Training Performance*

Table 10 Training Performance

Metric	Value
Training Accuracy	99.52%
Validation Accuracy	98.91%
Testing Accuracy	99.10%
Training Loss	0.032
Validation Loss	0.041
Testing Loss	0.038

X. DISCUSSION

The prototype evaluation indicates that the proposed hybrid framework achieves superior classification performance compared with conventional CNN, MobileNetV3, and ResNet50 architectures. EfficientNet-B3 extracts detailed local disease features, while the Vision Transformer captures long-range contextual information. Their combined feature representation improves recognition of visually similar diseases.

The integration of Grad-CAM and SHAP increases model transparency by highlighting the infected regions and identifying the factors that contribute to each prediction. This explainability can help farmers and agricultural experts understand the AI system's decisions and increase confidence in its recommendations.

The Organic Recommendation Engine further enhances the framework by providing disease-specific biological treatment suggestions, supporting sustainable

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farming practices and reducing dependence on synthetic pesticides.

➢ *Note:*

These observations are based on the prototype framework. Final conclusions should be drawn after experiments on the complete dataset.

XI. FUTURE SCOPE

➢ *The Proposed Framework Can Be Extended In Several Directions:*

- Develop an Android and iOS mobile application for field use.
- Deploy the model on edge AI devices such as NVIDIA Jetson Nano or Raspberry Pi.
- Integrate IoT sensors for real-time monitoring of environmental conditions.
- Use UAVs (drones) for large-scale orchard surveillance.
- Add disease severity estimation to support treatment prioritization.
- Expand the dataset to include additional diseases and geographical regions.
- Support multilingual recommendations for farmers.
- Incorporate weather forecasting to improve disease risk prediction.
- Enable cloud-based monitoring and advisory services.

XII. CONCLUSION

This research presents AgriVisionXAI, an Explainable Artificial Intelligence framework for early detection of jackfruit diseases and intelligent organic treatment recommendation using hybrid deep learning models. The proposed system combines EfficientNet-B3 and Vision Transformer to achieve accurate disease classification while integrating Grad-CAM and SHAP to provide transparent and interpretable predictions.

The framework includes image preprocessing, feature extraction, hybrid classification, explainable AI, and an Organic Recommendation Engine, creating a comprehensive decision-support system for precision agriculture. The prototype evaluation suggests that the hybrid architecture has the potential to outperform conventional deep learning models in terms of accuracy and interpretability.

By supporting timely disease diagnosis and environmentally friendly treatment recommendations, the proposed system can help reduce crop losses, improve fruit quality, and promote sustainable jackfruit cultivation. With further validation using real-world datasets and deployment in mobile or IoT platforms, AgriVisionXAI has the potential to become a practical tool for farmers and agricultural experts.

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➢ *Author Contributions*

Table 11 Author Contributions

Author	Contribution
Avala Sai Lokesh	Conceptualization, Literature Review, Dataset Collection, Data Preprocessing, Software Development, Hybrid Deep Learning Model Design, Experimental Analysis, Result Interpretation, Visualization, and Manuscript Preparation.
Dr. R. Sathya Janaki	Research Supervision, Methodology Validation, Technical Guidance, Manuscript Review and Editing, Critical Evaluation, and Overall Project Administration.

➢ *Conflict of Interest*

The authors declare that there is no conflict of interest regarding the publication of this research.

➢ *Data Availability Statement*

The dataset used in this research consists of images collected from jackfruit orchards, publicly available agricultural image repositories, and benchmark datasets. The processed dataset can be made available by the corresponding author upon reasonable request for academic and research purposes.

➢ *Ethical Approval*

This study does not involve human participants or animals requiring ethical approval. Image collection was conducted with permission from orchard owners and used solely for academic research purposes.

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