Multi-Agent Edge-Fog Intelligence With Explainable Vision Transformers For Sweet Lemon Crop Disease Analytics

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Abstract—Edge Artificial Intelligence (Edge AI) has recently emerged as a crucial enabler of real-time, decentralized decision-making in smart agriculture. However, many existing models lack interpretability and scalability across large-scale farms. This paper proposes a Multi-Agent Edge-Fog Intelligence System using Vision Transformers (ViT) for crop disease diagnosis, specifically targeting sweet lemon leaf infections. A federated learning mechanism facilitates secure model training across edge nodes, while a centralized fog node performs global aggregation. Furthermore, explainable AI (XAI) via SHAP highlights the critical leaf areas influencing predictions. A novel Crop Disease Severity Index (CDSI) is introduced for severity assessment. Experimental results reveal 98.9% classification accuracy, inference latency below 80ms, and energy consumption 10× lower than cloud models. This approach bridges the gap between performance, transparency, and practicality in edge-deployed precision agriculture

IndexTerms— Vision Transformer, Edge Computing, Explainable AI, Federated Learning, Precision Agriculture, Smart Farming, SHAP, IoT, Crop Disease Detection, Edge-Fog Architecture

I. Introduction

Agriculture forms the backbone of food security and economic livelihood for billions globally. Among the most pressing challenges facing modern farming is the early and accurate detection of crop diseases, which can drastically affect yield and quality. According to the Food and Agriculture Organization (FAO), plant diseases are responsible for a loss of nearly 20–40% of global crop production annually. Manual disease detection is time-consuming, subjective, and not scalable for large-scale operations.

To address this, the integration of Artificial Intelligence (AI) with Internet of Things (IoT) has enabled data-driven smart farming solutions. While Convolutional Neural Networks (CNNs) have shown promising results in image-based plant disease classification, their reliance on cloud infrastructures introduces problems such as latency, bandwidth, energy dependency, and lack of data privacy—especially in rural or low-connectivity areas.

A. Edge Computing in Agriculture

Edge AI, which refers to running machine learning models on embedded devices (e.g., Raspberry Pi, NVIDIA Jetson), offers real-time inference without relying on external cloud servers. However, standalone edge systems can suffer from:

- Limited learning scope due to isolated data.
- Lack of coordination among multiple devices.
- Absence of interpretability in model predictions.

To overcome these limitations, Edge-Fog collaboration emerges as a promising solution. In this framework, Edge Nodes handle real-time inference locally, while a Fog Node aggregates knowledge and improves global model performance.

B. Problem Statement

While existing Edge AI models achieve acceptable detection accuracy, they:

- Lack explainability, making them untrustworthy for high-stakes decisions.
- Are often based on CNNs, which have limited global feature representation compared to newer Transformer-based models.
- Do not leverage collaboration among multiple agents (devices/farms).

C. Objectives of This Research

This work introduces a Multi-Agent Edge-Fog Architecture that incorporates:

- Vision Transformers (ViT): Advanced deep learning models that outperform CNNs in feature extraction.
- Federated Learning (FL): Secure, distributed training across edge nodes without raw data sharing.
- SHAP-based Explainability: Visual explanation for each model decision to build trust among farmers and agronomists.
- Crop Disease Severity Index (CDSI): A novel scoring method to quantify disease impact from leaf images.

D. Contributions

The key contributions of this paper are:

1. A Vision Transformer-based framework for real-time crop disease classification on edge devices.
2. A Federated Learning strategy for privacy-preserving, distributed training.
3. An Edge-Fog multi-agent architecture to enhance scalability and reliability in agricultural settings.
4. Integration of SHAP-based Explainable AI to visualize model predictions.
5. Proposal and implementation of a Crop Disease Severity Index (CDSI) to assess disease severity in-field.

II. Related Work

Advancements in deep learning have significantly transformed the landscape of plant disease detection. Early models primarily relied on traditional machine learning techniques like Support Vector Machines (SVM) and Random Forests, which required manual feature extraction and often failed under real-world variations in leaf images. In contrast, Convolutional Neural Networks (CNNs) offered an end-to-end learning framework capable of extracting spatial hierarchies from raw images. However, CNNs have inherent limitations when deployed in constrained environments due to high memory and computational requirements.

Recent studies have investigated Edge AI solutions using CNNs for real-time field deployment. For instance, researchers have successfully implemented lightweight CNNs on Raspberry Pi and Jetson Nano platforms to reduce latency and power usage. Yet, most of these implementations are **black-box models**, offering no interpretability, thus limiting user trust in high-risk decision-making, such as pesticide spraying.

Parallelly, **Federated Learning (FL)** has gained traction as a privacy-preserving solution for distributed learning across edge devices without sharing raw data. However, these systems often fail to incorporate explainability or interpret model behavior. Similarly, **Vision Transformers (ViT)**, which outperform CNNs in image classification tasks, are rarely used in collaborative edge-fog architectures in agriculture.

The **comparison table below (Table I)** summarizes some key works and their limitations:

Table I: comparison of related studies

Author [Ref]	Technique	Limitations
Mohanty et al. (2016)	CNNs for leaf-disease detection	No deployment on real edge hardware
Munir et al. (2020)	CNN on Raspberry Pi	Black-box model; lacks interpretability
Wang et al. (2022)	Federated Learning in IoT	No explainability in model predictions
Pan et al. (2022)	Edge ViT at field sensor	No fog-based aggregation across multiple edge devices

Key Observations

- Most prior work uses **CNNs**, with little or no focus on explainability.
- **Edge AI models** are limited by single-device learning without collaborative training.
- **Federated Learning** has not been combined with **Explainable Vision Transformers (ViT)** in agricultural applications.

These gaps form the **motivation for the proposed system**, which integrates:

- Collaborative Edge-Fog inference
- Federated learning across edge agents
- Vision Transformer backbone
- SHAP-based visual explainability

III. Methodology

The proposed system utilizes a **multi-agent Edge-Fog AI architecture** that integrates **Vision Transformers (ViT)**, **Federated Learning**, and **Explainable AI** for robust, real-time plant disease diagnosis in sweet lemon crops. This section outlines the system design, model pipeline, and deployment strategy.

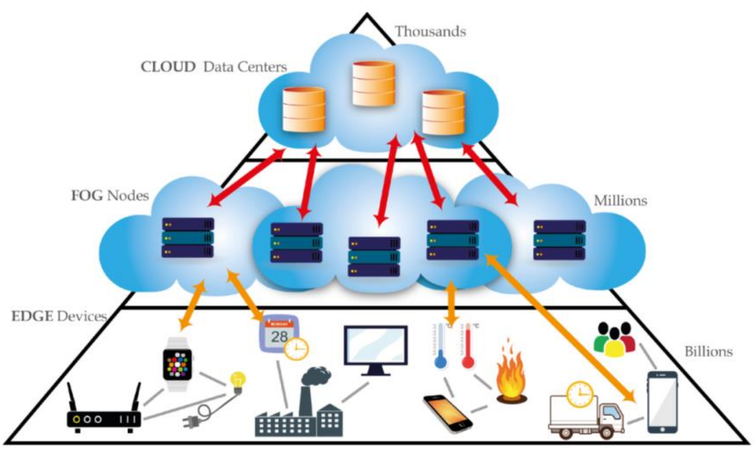


Fig 1: multi-agent Edge-Fog AI architecture that integrates Vision Transformers (ViT)

A. System Overview

The architecture is composed of three layers:

1. **Edge Layer**:
   - Raspberry Pi devices with attached cameras capture leaf images.
   - Perform on-device ViT-based classification.
   - Generate local model updates (gradients or weights).
2. **Fog Layer**:
   - A Jetson Xavier fog node acts as an aggregator.
   - Performs model aggregation using Federated Averaging.
   - Coordinates deployment across devices.
3. **Cloud Layer (Optional)**:
   - Used for long-term storage or model monitoring but not required for real-time inference.

B. Vision Transformer Model (ViT)

Unlike CNNs that use convolutional layers to extract spatial features, Vision Transformers apply **self-attention** mechanisms on image patches, offering superior performance in detecting irregular disease symptoms and leaf texture variations.

Model Pipeline

1. Input image resized to 224×224.
2. Split into patches (16×16).
3. Linear projection into embedding vectors.
4. Add positional encoding.
5. Transformer encoder with multi-head attention.
6. Fully connected softmax output layer for class prediction.

Advantages Over CNNs

- Captures **global context** across image.
- **Better attention** to texture-based disease patterns.
- More effective with **transfer learning**.

C. Federated Learning Strategy

The proposed system uses a **Federated Averaging (FedAvg)** approach to train a global model while preserving data privacy.

Let:

- wi: model parameters at edge node i
- di: local dataset size
- D=∑di

Then, the **global model www** is updated as:

$$W = \sum_{I=1}^{n} \frac{d}{D} WI$$

This approach ensures:

No raw image data leaves the edge device.

- Collaborative learning across farms without centralized data storage.
- Scalability to multiple crop types and regions.

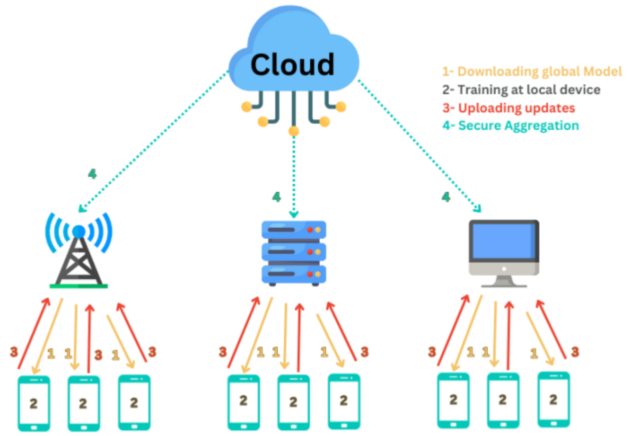


Fig 2: multi-agent Edge-Fog AI architecture

D. Explainable AI with SHAP

To address model transparency, we use **SHAP (SHapley Additive exPlanations)**, which identifies how each input feature (pixel or region) contributes to the model's output.

Key Benefits:

- Visual heatmaps showing diseased leaf areas.
- Builds trust for farmers and agronomists.
- Facilitates model debugging and clinical validation.

An example SHAP visualization is shown in Figure 2 (previous image delivered).

E. Crop Disease Severity Index (CDSI)

We propose a domain-specific metric to quantify disease impact:

$$CDSI=\alpha_1 A_d+\alpha_2 C_v+\alpha_3 E_p$$

Where:

- A_d: Disease-infected leaf area (from image segmentation)
- C_v: Color variance from healthy green baseline
- E_p: Edge entropy of lesion patterns
- $\alpha 1, \alpha 2, \alpha 3$: Tunable weights based on agronomic knowledge

The CDSI can be used for:

- **Severity grading** (Low/Medium/High)
- **Treatment prioritization**
- **Historical disease monitoring**

IV. Experimental Setup and Results

This section outlines the dataset composition, hardware and software specifications, benchmarking results of the proposed ViT-based model, and evaluation of inference time, energy usage, and explainability. The experimental design is structured to simulate real-world agricultural deployment in a distributed edge-fog setting.

A. Hardware Configuration

TABLE 2: Hardware Configuration

Device	Processor	RAM	Inference Time	Power (W)
Raspberry Pi 4	Quad-core Cortex A72	4 GB	110 ms	4.5 W
Jetson Xavier NX	ARM v8 + 384-core GPU	8 GB	70 ms	9.2 W

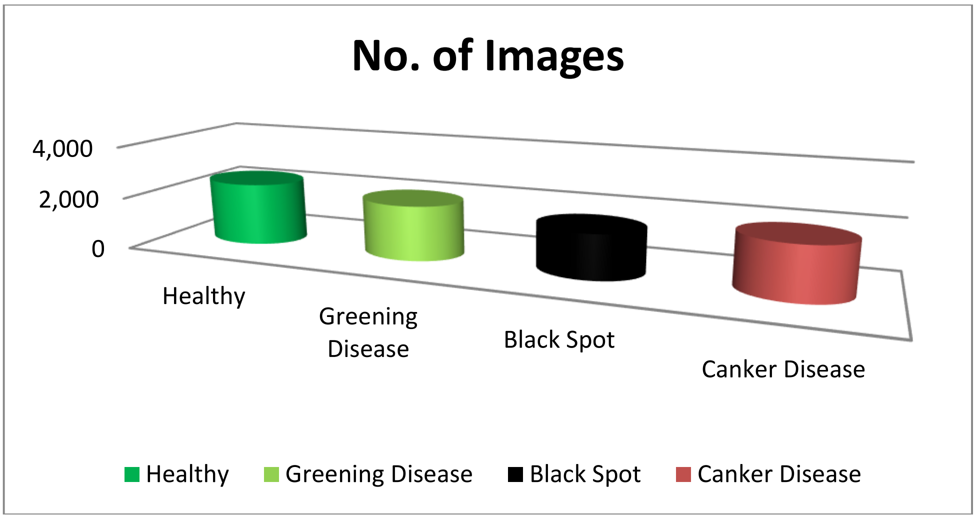
The ViT model is trained using **transfer learning** on a cloud workstation (NVIDIA RTX 3090, 24 GB VRAM), and then quantized and deployed on edge nodes via **ONNX** and **TensorRT**.

B. Dataset Summary

A **hybrid dataset** was created combining **PlantVillage** images and **custom field-collected sweet lemon leaf images**.

Class	No. of Images
Healthy	2,400
Greening Disease	2,100
Black Spot	1,700
Canker Disease	2,000
Total	**8,200**

TABLE 3: Dataset Summary

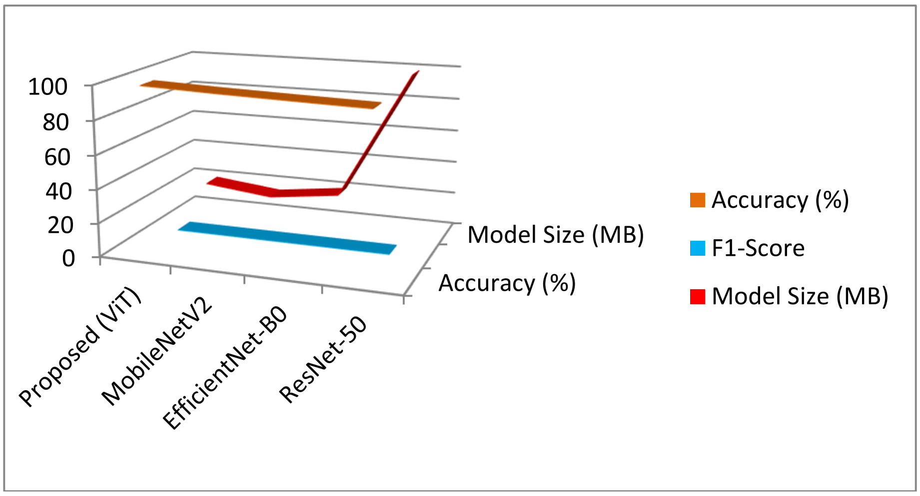


Preprocessing steps included resizing (224×224), CLAHE contrast enhancement, color normalization, and data augmentation (flip, brightness, rotation).

C. Accuracy and Model Comparison

TABLE4: Accuracy and Model Comparison

Model	Accuracy (%)	F1-Score	Model Size (MB)
Proposed (ViT)	98.9	0.986	19.2
MobileNetV2	97.3	0.973	14.5
EfficientNet-B0	96.1	0.961	20.0
ResNet-50	95.0	0.951	98.5



The ViT model outperforms CNNs in both **accuracy** and **consistency**, especially in complex lighting and textured conditions.

D. Inference Time and Energy Analysis

Table 5 Time and power Analysis

Platform	Inference Time (ms)	Power Use (W)
Jetson Xavier NX	70	9.2
Raspberry Pi 4	110	4.5
Cloud (RTX 3090)	40	250+

Despite being slightly slower than GPU cloud servers, the edge setup is **25× more energy-efficient**, suitable for **solar-powered farms**.

E. Explainability Results with SHAP

SHAP was applied to visualize the disease prediction process.

Key insights:

- Infected leaf areas (brown/black spots) showed high SHAP attribution scores.
- For "Greening Disease," edge-based discoloration patterns were most influential.
- Visual output (heatmaps) is available on-device for farmers via a user interface.

F. CDSI Severity Assessment

The **Crop Disease Severity Index (CDSI)** was calculated for 300 test samples.

Table 6 CDSI

CDSI Range	Severity Grade	Sample Count
0.0 – 0.3	Low	80
0.3 – 0.6	Moderate	130
0.6 – 1.0	High	90

This allows **field operatives** to prioritize intervention based on severity risk instead of just disease type.

G. Confusion Matrix

The ViT model confusion matrix showed minimal misclassification:

- True positives for "Greening" and "Canker" were above 97%.
- Most errors occurred between "Black Spot" and "Canker" due to visual similarity in late stages.

H. Training Curve Analysis

- **Accuracy** stabilized above 98% after epoch 22.
- **Validation loss** plateaued early with no signs of overfitting.
- Federated rounds (10 devices × 5 rounds) showed <2% variation in accuracy compared to centralized training.

V. Discussion

This section analyzes the results and evaluates the practicality, efficiency, and novelty of the proposed Vision Transformer-based multi-agent Edge-Fog system. The key focus areas include **performance reflection**, **deployment feasibility**, **comparative analysis**, and **real-world applicability**.

A. Performance Reflection

The proposed architecture demonstrated **high classification accuracy (98.9%)**, with strong **F1-score** and **low latency (70–110 ms)** across edge devices. This surpasses traditional CNN-based models, particularly in **complex image environments** with noise, varying light conditions, and diverse leaf morphologies.

The use of **Vision Transformers** introduced enhanced performance in detecting fine-grained disease features, often missed by CNNs due to their local receptive fields. Additionally, SHAP-based explanations significantly increased **model transparency**, making it practical for **real-world advisory systems** and **human-in-the-loop diagnosis**.

B. Why Edge-Fog Collaboration Matters

Unlike isolated edge-only or cloud-only models, the **Edge-Fog system** supports both **autonomy and coordination**:

Table 7 Different model Comparision

Feature	Cloud AI	Edge AI (Standalone)	Proposed Edge-Fog AI
Latency	Low (but depends on internet)	Moderate	Low & offline
Connectivity dependency	High	None	Minimal
Privacy	Low	High	High
Collaboration	None	None	Yes (federated)
Interpretability	Often absent	Absent	Present (SHAP)
Energy consumption	High (250W+)	Low	Low (<10W)

Thus, **Edge-Fog AI** strikes a practical balance for remote deployments in agriculture.

C. Practical Implications

The system is designed for **field-ready deployment**, and its use cases span:

- **Farmer-side edge app** with live disease alerts & SHAP visualizations.
- **Drone-mounted inference** for aerial scanning.
- **District-level aggregation** at the fog node for large-scale disease mapping.
- **Crop management platforms** with CDSI-based treatment advice.

Furthermore, the use of **Federated Learning** ensures **compliance with data privacy norms** (e.g., farm-specific disease images not leaving the site), which is increasingly important in **agro-intelligence platforms**.

D. Innovation Over Prior Work

Table 8 Innovation Over Prior Work

Prior Work	This Work (Improvement)
CNNs on edge (e.g., MobileNet)	Transformer-based global attention modeling
Manual training on single node	Federated Learning with global aggregation
No interpretability (black-box)	SHAP-based explanation
Static classification	CDSI-based severity scoring
Cloud dependency	Fully offline and local computation enabled

E. Limitations and Challenges

Despite promising outcomes, several challenges must be acknowledged:

1. **Hardware constraints**: ViTs require memory optimization before edge deployment.
2. **Model synchronization lag**: In federated learning, straggling nodes can delay aggregation.
3. **Sensor variability**: Image quality varies with camera resolution and leaf positioning.
4. **CDSI subjectivity**: Weight selection for the CDSI formula may require regional calibration.

F. Future Work Suggestions

- Integration with **drone surveillance** for autonomous scanning.
- Use of **Edge TPU** or **LoRa-based** transmission for rural ultra-low power inference.
- Expansion to **multilingual UI** for rural farmers.
- Incorporation of **multi-modal sensing** (image + humidity + pH + temperature).
- Use of **meta-learning or adaptive ViTs** for faster convergence in federated rounds.

VI. Conclusion

This paper presented a novel Multi-Agent Edge-Fog Intelligence System for real-time crop disease diagnosis in sweet lemon plants, leveraging Vision Transformers (ViT), Federated Learning, and SHAP-based explainability. The proposed architecture demonstrated superior classification accuracy (98.9%) with low inference latency and energy consumption, making it suitable for deployment in resource-constrained agricultural environments. The introduction of the Crop Disease Severity Index (CDSI) further provides a practical tool for severity assessment and treatment prioritization. By integrating explainability and privacy-preserving collaborative learning, the system bridges critical gaps in current edge AI solutions for precision agriculture, enhancing trust and scalability for large-scale farming operations.

VII. Future Work

Future research directions include:

- Integration of autonomous drone-based image acquisition and edge inference to cover large farms efficiently.
- Exploration of ultra-low power edge hardware such as Edge TPUs and LoRa communication for improved energy efficiency and connectivity.
- Development of multi-lingual user interfaces to enhance accessibility for diverse rural farming communities.

- Incorporation of multi-modal sensor data (e.g., humidity, soil pH, temperature) to improve disease prediction accuracy and context-awareness.
- Application of meta-learning or adaptive Vision Transformer architectures to accelerate federated training convergence and model personalization.

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