Explainable Graph Neural Network Framework for Multimodal Early Plant Disease Prediction

Silambarasan G[1], Dr. I. Laurence Aroquiaraj[2]
[1]*Research Scholar, Department of Computer Science, Periyar University, Salem.*
[2]*Professor, Department of Computer Science, Periyar University, Salem.*

***Abstract*—Early detection of plant diseases is critical for improving crop productivity, reducing agricultural losses, and supporting sustainable farming practices. Traditional plant disease detection methods predominantly rely on visual inspection of leaf symptoms or image-based deep learning models, which often identify diseases only after visible damage has occurred. Such reactive approaches limit the ability of farmers and agricultural systems to perform timely interventions. To address this limitation, this study proposes an explainable graph neural network framework for multimodal early plant disease prediction that integrates heterogeneous agricultural data sources and models the complex interactions between environmental conditions, soil parameters, and plant physiological responses. The proposed framework combines multimodal sensing data, including soil sensor measurements, environmental monitoring variables, plant physiological indicators, and image-derived features, into a unified graph-based representation of plant health dynamics. A graph neural network is employed to learn relational dependencies among plant health indicators, enabling the model to capture complex interactions that influence disease development. In addition, an explainable artificial intelligence module is incorporated to provide interpretable insights into the factors contributing to disease predictions, highlighting key environmental conditions and physiological signals associated with plant stress. Experimental evaluation demonstrates that the proposed framework achieves high predictive performance and improved interpretability compared with conventional machine learning and deep learning approaches. The integration of multimodal data and graph-based relational learning enables early detection of plant stress conditions before visible disease symptoms emerge. (Wang et al., 2025)The explainability component further enhances transparency and supports agronomic decision-making by identifying the underlying causes of plant health deterioration. Overall, the proposed approach provides a scalable and intelligent solution for next-generation precision agriculture systems, enabling proactive plant health monitoring and data-driven crop management strategies.**

***Index Terms*— Plant disease prediction; Graph neural networks; Multimodal learning; Explainable artificial intelligence; Precision agriculture; Agricultural sensor networks; Plant health monitoring; Deep learning in agriculture.**

I. INTRODUCTION

Global agriculture faces increasing challenges due to plant diseases that significantly reduce crop yield, food quality, and economic sustainability. According to recent agricultural studies, plant diseases are responsible for approximately 20 – 40% of global crop losses annually, posing a major threat to food security and agricultural productivity. Early detection of plant diseases is therefore essential for enabling timely intervention, reducing pesticide usage, and improving sustainable crop management practices. However, conventional disease detection methods primarily rely on visual inspection of leaf symptoms or laboratory-based pathogen identification, which often occur only after the disease has progressed to advanced stages. Recent advancements in artificial intelligence and deep learning have significantly improved plant disease detection systems. Convolutional Neural Networks (CNNs) and other deep learning models have demonstrated high accuracy in identifying plant diseases using leaf images. Large-scale datasets such as Plant Village have enabled the development of automated disease classification systems capable of recognizing numerous crop diseases across multiple plant species. Despite these advances, most existing approaches focus on analysing visible symptoms on plant leaves and therefore function primarily as reactive diagnostic tools rather than predictive disease monitoring systems. In real agricultural environments, diseases frequently originate from root-zone stress, soil pathogens, or environmental conditions long before visible symptoms appear on leaves.(Roumeliotis et al., 2023)

Plants operate as complex biological systems where stress signals propagate through internal vascular communication networks consisting of xylem and phloem tissues. These vascular pathways transport water, nutrients, hormones, and electrical signals that coordinate physiological responses between roots, stems, and leaves. When pathogens or environmental stress affect the root zone, biochemical and hydraulic signals travel through the vascular system, triggering systemic responses in aerial plant tissues. Although plant physiology research has extensively studied these signaling mechanisms, most existing computational disease detection systems do not explicitly incorporate plant vascular communication processes. As a result, current artificial intelligence models often treat the plant as a black box, ignoring the biological pathways through which disease signals propagate. Another important limitation of current plant disease detection systems is their reliance on single data modalities, particularly leaf images. In practical agricultural environments, plant health is influenced by multiple interacting factors including soil moisture, nutrient levels, temperature, humidity, microbial activity, and environmental conditions. (Under Review in IEEE Transactions, n.d.)Modern precision agriculture systems increasingly deploy Internet of Things (IoT) sensors, hyperspectral cameras, and environmental monitoring systems to capture diverse sources of plant health information. However, effectively integrating these heterogeneous data sources into a unified disease prediction framework remains a major challenge. Multimodal learning approaches provide an opportunity to combine complementary information from different sensing modalities, enabling a more comprehensive understanding of plant health dynamics.(Tanwar & Singh, 2023)

Graph-based modelling has recently emerged as a powerful paradigm for representing complex systems with interconnected components. Graph Neural Networks (GNNs) extend traditional deep learning architectures by enabling learning on graph-structured data, where nodes represent entities and edges represent relationships between them. In the context of plant disease prediction, the plant vascular system, environmental sensors, and spatial crop structures can naturally be represented as graphs. By modelling the plant as a physiological communication network, GNNs can capture spatial interactions between roots, vascular pathways, and leaf tissues, enabling more realistic modelling of disease propagation mechanisms. Despite their potential, the application of graph neural networks in plant disease intelligence and precision agriculture remains relatively unexplored. In addition to predictive accuracy, the interpretability of artificial intelligence models is becoming increasingly important in agricultural decision-making. Farmers, agronomists, and agricultural researchers require transparent explanations of model predictions to understand the underlying factors contributing to plant stress and disease. Many deep learning models operate as black-box systems, making it difficult to identify which environmental conditions, physiological signals, or plant structures influence the prediction outcomes. Explainable Artificial Intelligence (XAI) techniques aim to address this limitation by providing interpretable insights into model behaviour, enabling users to understand the importance of specific features and relationships within the prediction process. Integrating explainability into plant disease prediction systems can enhance trust, support agronomic decision-making, and facilitate practical deployment in precision agriculture environments.

To address these challenges, this study proposes an explainable graph neural network framework for multimodal early plant disease prediction. The proposed approach integrates heterogeneous agricultural data sources, including soil sensor measurements, environmental parameters, and plant physiological indicators, within a graph-based representation of plant health dynamics. Graph neural networks are employed to model spatial and relational dependencies between plant components and environmental factors, enabling the system to capture complex interactions that influence disease development. Furthermore, explainable AI mechanisms are incorporated to provide interpretable insights into the factors driving disease predictions, helping stakeholders understand the relationships between environmental stress conditions and plant physiological responses. The proposed framework aims to move beyond traditional symptom-based disease detection by enabling predictive plant health monitoring based on multimodal agricultural data and physiological communication modelling. By combining graph neural networks, multimodal data integration, and explainable artificial intelligence, this research contributes toward the development of intelligent and transparent plant disease prediction systems capable of supporting next-generation precision agriculture and sustainable crop management.(Zainab & Mahum, 2025a)

II.LITERATURE REVIEW

The proposed research introduces several novel contributions that distinguish it from existing plant disease detection approaches.

First, the study proposes a multimodal plant health monitoring framework that integrates heterogeneous agricultural data sources, including soil sensor measurements, environmental monitoring variables, plant physiological indicators, and image-derived features. Unlike traditional approaches that rely solely on leaf image analysis, the proposed framework captures a more comprehensive representation of plant health dynamics by combining multiple modalities of agricultural data.(Devarajan et al., 2026a)

Second, the research introduces a graph neural network–based modelling approach to represent plant health systems as relational networks. In this framework, plant components, environmental variables, and sensor observations are modelled as nodes within a graph structure, while the interactions between these components are represented as edges. This graph-based representation enables the model to capture complex dependencies between environmental conditions and plant physiological processes, allowing more realistic modelling of disease propagation mechanisms.

Third, the proposed system incorporates multimodal time-series analysis to identify early plant stress signals that may precede visible disease symptoms. By analysing temporal patterns across multiple agricultural data streams, the framework enables proactive plant health monitoring and early disease detection.

Fourth, the study integrates explainable artificial intelligence techniques into the graph neural network framework. The explainability component identifies the most influential environmental variables, physiological indicators, and relational interactions contributing to disease prediction outcomes. This capability enhances transparency and provides valuable insights for farmers, agronomists, and agricultural researchers.

Finally, the proposed framework contributes to the advancement of precision agriculture systems by providing a scalable and interpretable model capable of supporting intelligent crop monitoring and data-driven decision-making. By combining multimodal learning, graph-based relational modelling, and explainable AI, the research presents a comprehensive approach to early plant disease prediction that extends beyond the capabilities of existing image-based detection systems.

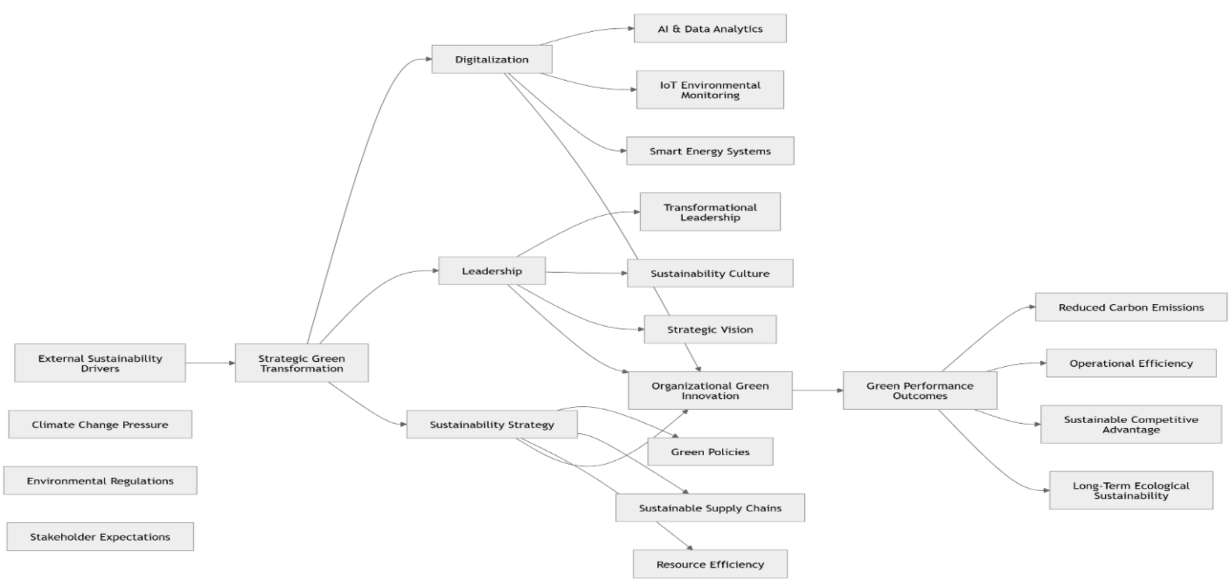

Figure: 1 Conceptual framework of strategic green transformation

III. RESEARCH CONTRIBUTIONS

This study introduces an advanced artificial intelligence framework for early plant disease prediction by integrating multimodal agricultural data, graph-based relational modelling, and explainable machine learning techniques. Unlike conventional plant disease detection systems that rely primarily on leaf image analysis and visible symptoms, the proposed framework explicitly models complex interactions between plant physiological processes and environmental conditions. (G. Prasadu et al., 2025)

The key contributions of this research are summarized as follows:

1. Graph-Based Modelling of Plant Health Dynamics
This research introduces a novel graph-based representation of plant health systems, where plant components, environmental factors, and sensor observations are modelled as interconnected nodes within a graph structure. The proposed Graph Neural Network (GNN) architecture captures spatial and relational dependencies among soil conditions, environmental variables, and plant physiological responses. By modelling plant health as a dynamic relational network, the framework enables more realistic representation of disease propagation mechanisms compared to traditional independent-feature learning models.

2. Multimodal Agricultural Data Fusion Framework
The study proposes a multimodal data integration approach that combines heterogeneous agricultural data sources, including soil sensor measurements, environmental monitoring data, and plant physiological indicators. This multimodal fusion enables the model to capture complementary information from different sensing modalities, improving the robustness and predictive accuracy of plant disease detection systems in real agricultural environments where plant health is influenced by multiple interacting factors.(Devarajan et al., 2026b)

3. Early Disease Prediction through Relational Learning
The proposed framework enables early detection of plant disease by learning complex relationships among environmental stress conditions, plant physiological signals, and disease development patterns. By leveraging graph-based relational learning, the model can identify subtle stress signals and interdependencies between plant components that precede visible disease symptoms, enabling predictive plant health monitoring and proactive crop management.

4. Integration of Explainable Artificial Intelligence (XAI)
To address the black-box nature of deep learning models, the proposed framework incorporates explainable artificial intelligence techniques to interpret disease prediction results. The explain ability module identifies the most influential features, environmental variables, and relational pathways contributing to model predictions. This transparency enhances trust in the system and supports agronomists and farmers in understanding the underlying causes of plant stress and disease development.

5. Scalable Framework for Intelligent Precision Agriculture
The proposed explainable graph neural network framework provides a scalable and adaptable architecture for intelligent agricultural monitoring systems. By integrating multimodal sensing, relational modelling, and explainable decision support, the framework contributes to the development of next-generation precision agriculture technologies capable of supporting sustainable crop management and large-scale plant health monitoring.

IV. LITERATURE REVIEW

4.1 Deep Learning Approaches for Plant Disease Detection

Recent advances in artificial intelligence have significantly transformed plant disease detection and monitoring systems. Traditional machine learning techniques initially relied on handcrafted image features extracted from plant leaves, such as colour histograms, texture descriptors, and shape-based features. These features were then used with classifiers such as support vector machines, decision trees, or k-nearest neighbours to identify disease patterns. While these methods demonstrated moderate success under controlled conditions, their performance was often limited by environmental variability, illumination changes, and complex backgrounds present in real agricultural environments.(Zainab & Mahum, 2025b)

The emergence of deep learning techniques, particularly convolutional neural networks, has greatly improved the capability of automated plant disease detection systems. Deep learning models automatically learn hierarchical feature representations from raw images, enabling the identification of complex disease patterns that are difficult to capture using handcrafted features. Modern architectures have achieved high classification accuracy in detecting plant diseases across multiple crop species. However, most existing deep learning models rely primarily on visible leaf symptoms and therefore operate as reactive diagnostic tools. In practical agricultural settings, disease symptoms often appear only after the infection has already progressed, limiting the effectiveness of such approaches for early intervention.

Another limitation of image-based disease detection system is their reliance on controlled datasets that contain well-cantered leaf images with minimal background noise. When deployed in real field conditions, these models frequently experience performance degradation due to varying lighting conditions, occlusions, and environmental disturbances. These challenges highlight the need for more robust disease prediction systems capable of incorporating multiple sources of plant health information beyond visual symptoms.

4.2 Multimodal Learning in Precision Agriculture

To address the limitations of single-modality approaches, recent research has explored the integration of multiple data sources for plant health monitoring. Modern precision agriculture systems employ a wide range of sensing technologies including soil sensors, environmental monitoring devices, hyperspectral cameras, and remote sensing platforms. These technologies provide diverse information about plant health, such as soil moisture levels, nutrient availability, temperature, humidity, and plant physiological responses.(Devarajan et al., 2026c)

Multimodal learning approaches aim to combine these heterogeneous data sources to improve predictive performance. By integrating information from multiple modalities, machine learning models can capture complex relationships between environmental conditions and plant stress responses. For example, soil nutrient deficiencies or water stress may influence plant health long before visible symptoms appear on leaves. Incorporating such information into predictive models enables earlier detection of plant stress and disease conditions.

Despite the advantages of multimodal learning, integrating heterogeneous agricultural data presents several challenges. Different data modalities often have varying temporal resolutions, spatial scales, and measurement uncertainties. Additionally, effectively capturing the interactions between environmental factors and plant physiological processes requires models capable of learning complex relational structures. Many existing multimodal systems rely on simple feature concatenation strategies, which may fail to capture deeper relationships between different data sources. Therefore, more sophisticated modelling approaches are required to represent the interconnected nature of plant health dynamics.(References, n.d.)

4.3 Graph Neural Networks for Modelling Complex Systems

Graph-based learning has emerged as a powerful paradigm for modelling complex systems characterized by interconnected components. Unlike traditional machine learning models that operate on independent feature vectors, graph neural networks enable learning on graph-structured data where relationships between entities play a central role. In a graph representation, nodes represent individual entities and edges represent relationships or interactions between them.

Graph neural networks have demonstrated strong performance in various domains involving relational data, including social networks, transportation systems, molecular biology, and recommendation systems. Their ability to capture spatial dependencies and relational interactions makes them particularly suitable for modelling complex biological systems. In the context of agriculture, plant physiological processes and environmental interactions naturally form network structures. For instance, plant components such as roots, stems, and leaves interact through vascular communication pathways, while environmental factors influence plant health through interconnected ecological processes.(Bhujel et al., 2022a)

By representing plant health dynamics as a graph structure, graph neural networks can capture spatial relationships between plant components and environmental factors. This approach enables more realistic modelling of disease propagation mechanisms and plant stress responses. However, the application of graph neural networks in plant disease prediction remains relatively limited, and existing research has primarily focused on image-based disease classification rather than relational modelling of plant health systems.

4.4 Explainable Artificial Intelligence in Agricultural Applications

Although deep learning models have achieved remarkable performance in many agricultural applications, their lack of interpretability remains a significant concern. Most deep learning models operate as black-box systems, making it difficult for users to understand how predictions are generated. In agricultural decision-making, interpretability is particularly important because farmers and agronomists need to understand the underlying causes of plant stress or disease to implement effective management strategies.

Explainable Artificial Intelligence aims to address this limitation by providing insights into the internal decision-making processes of machine learning models. Explainability techniques help identify the most influential features contributing to model predictions and reveal the relationships between input variables and output outcomes. In plant disease prediction systems, explainable models can highlight key environmental factors, soil conditions, or physiological signals that indicate the presence of plant stress.

Integrating explain ability into agricultural artificial intelligence systems enhances transparency and increases user trust in automated decision-support tools. Furthermore, explainable models can provide valuable scientific insights into plant health dynamics by identifying patterns and relationships that may not be easily observable through traditional experimental methods.

4.5 Research Gap

The existing approaches rely heavily on image-based disease classification, which limits their ability to detect early-stage infections before visible symptoms appear. Furthermore, many current models treat plant health indicators as independent variables and fail to capture the complex relational interactions between environmental conditions, plant physiology, and disease development. Although multimodal agricultural sensing systems provide diverse sources of plant health information, effectively integrating these heterogeneous data streams remains a major challenge. Existing multimodal models often lack mechanisms for representing relational dependencies between different data modalities. In addition, the interpretability of deep learning models remains limited, restricting their practical adoption in agricultural decision-making. Such systems can provide more accurate, interpretable, and proactive plant disease prediction capabilities, supporting the development of advanced precision agriculture technologies. The proposed research introduces several novel contributions that distinguish it from existing plant disease detection approaches.(Roumeliotis et al., 2024)

First, the study proposes a multimodal plant health monitoring framework that integrates heterogeneous agricultural data sources, including soil sensor measurements, environmental monitoring variables, plant physiological indicators, and image-derived features. Unlike traditional approaches that rely solely on leaf image analysis, the proposed framework captures a more comprehensive representation of plant health dynamics by combining multiple modalities of agricultural data.

Second, the research introduces a graph neural network–based modelling approach to represent plant health systems as relational networks. In this framework, plant components, environmental variables, and sensor observations are modeled as nodes within a graph structure, while the interactions between these components are represented as edges. This graph-based representation enables the model to capture complex dependencies between environmental conditions and plant physiological processes, allowing more realistic modelling of disease propagation mechanisms.

Third, the proposed system incorporates multimodal time-series analysis to identify early plant stress signals that may precede visible disease symptoms. By analysing temporal patterns across multiple agricultural data streams, the framework enables proactive plant health monitoring and early disease detection.

Fourth, the study integrates explainable artificial intelligence techniques into the graph neural network framework. The explainability component identifies the most influential environmental variables, physiological indicators, and relational interactions contributing to disease prediction outcomes. This capability enhances transparency and provides valuable insights for farmers, agronomists, and agricultural researchers.

Finally, the proposed framework contributes to the advancement of precision agriculture systems by providing a scalable and interpretable model capable of supporting intelligent crop monitoring and data-driven decision-making. By combining multimodal learning, graph-based relational modelling, and explainable AI, the research presents a comprehensive approach to early plant disease prediction that extends beyond the capabilities of existing image-based detection systems.(Faheem Saidahmd et al., 2025)

V. METHODOLOGY

5.1 Overview of the Proposed Framework

The proposed framework aims to predict plant diseases at an early stage by integrating heterogeneous agricultural data sources and modelling their interactions using graph neural networks. Unlike conventional plant disease detection systems that rely primarily on leaf image analysis, the proposed architecture combines multiple data modalities representing environmental conditions, soil parameters, and plant physiological responses. These multimodal inputs are modelled within a graph-based structure to capture the complex relationships between plant health indicators.

The overall architecture consists of four major components:

1. Multimodal Data Acquisition and Pre-processing
2. Graph Construction and Representation Learning
3. Graph Neural Network–Based Disease Prediction
4. Explainable Artificial Intelligence Module

The proposed system learns the relational dependencies between plant components and environmental factors, enabling predictive modelling of disease development before visible symptoms appear.(Bhujel et al., 2022b)

5.2 Multimodal Data Acquisition and Pre-processing

Plant health is influenced by a variety of environmental and physiological factors. To capture these interactions, the proposed system integrates multiple data sources collected from agricultural monitoring systems.

Multimodal Data Sources

The framework considers the following modalities:

- Soil sensor data: soil moisture, pH level, nutrient concentration, and electrical conductivity
- Environmental data: temperature, humidity, rainfall, and solar radiation
- Plant physiological indicators: chlorophyll content, leaf temperature, and vegetation indices
- Leaf image features: visual symptoms extracted from plant leaf images

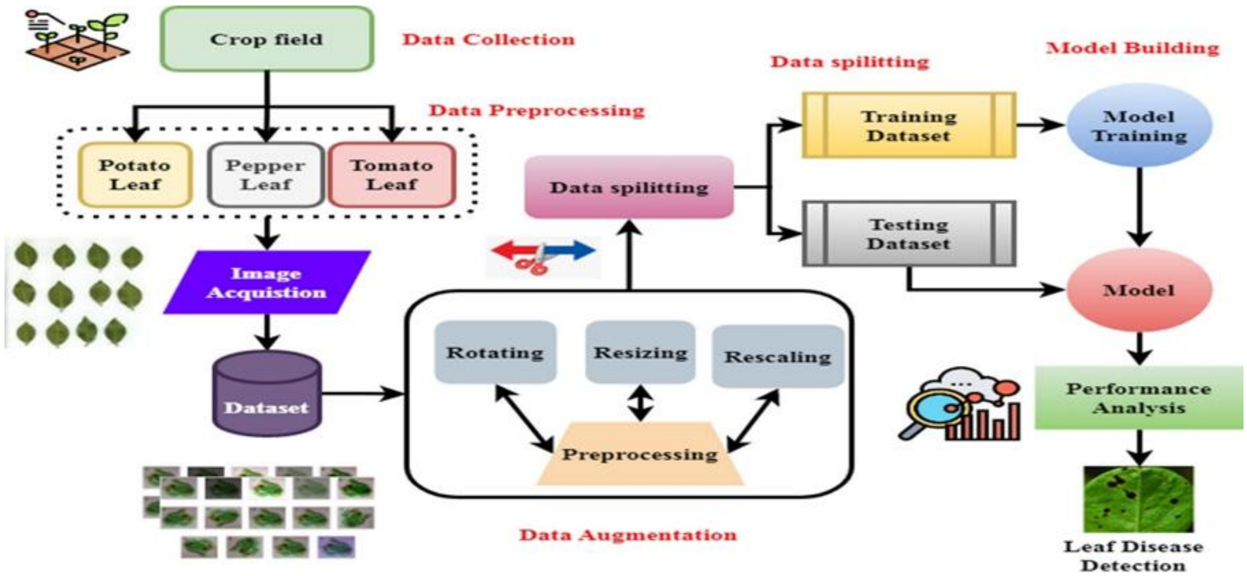

Figure:2. Data Augmentation

Each modality provides complementary information about plant health conditions. Soil and environmental data capture early stress conditions in the root zone, while leaf images represent visible manifestations of disease symptoms.

Data Pre-processing

Before constructing the graph model, the collected data undergo several Pre-processing steps:

1. Noise removal and data cleaning to eliminate sensor anomalies
2. Normalization of feature values to ensure consistent scaling across modalities
3. Feature extraction from leaf images using convolutional feature encoders
4. Temporal alignment of sensor data to synchronize observations across modalities

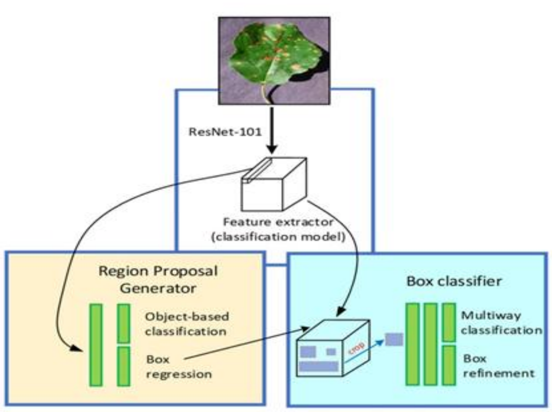

Figure 3. Deep learning–based object detection architecture for plant disease analysis

The resulting multimodal feature vectors are then used to construct the graph representation of plant health dynamics.

5.3 Graph Construction and Representation

To model the relational interactions among plant health indicators, the multimodal data are represented as a graph structure.

A graph is defined as:

$G = (V, E)$

where:

- V represents the set of nodes corresponding to plant components and sensor observations
- E represents the edges capturing relationships between nodes

Node Representation

Each node in the graph corresponds to a specific plant health entity or environmental measurement. Examples include:

- Soil conditions
- Environmental parameters
- Plant physiological indicators
- Leaf image features

Each node is associated with a feature vector:

$x_i \in \mathbb{R}^d$

where x_i represents the multimodal feature representation of node i.

Edge Construction

Edges represent interactions between nodes, capturing dependencies such as:

- Soil plant interactions
- environmental influence on plant physiology
- spatial relationships between plant components

The adjacency matrix A defines the connectivity between nodes:

$$A_{ij} = \begin{cases} 1, & \text{if node i is connected to node j} \\ 0, & \text{Otherwise} \end{cases}$$

5.4 Graph Neural Network for Disease Prediction

After constructing the graph structure, a Graph Neural Network is used to learn representations that capture interactions among nodes. The GNN updates node representations by aggregating information from neighbouring nodes.

For each node i, the representation update is defined as:

$$h_i^{k+1} = \sigma\left(\sum_{j \in N(i)} W^k \; h_j^k\right)$$

where:

- h_j^k represents the node embedding at layer k
- $N(i)$ denotes the set of neighbouring nodes
- W^k is the learnable weight matrix
- σ is a nonlinear activation function

Through multiple graph convolution layers, the model aggregates information from neighbouring nodes and learns high-level representations that capture plant health interactions.

The final graph representation is used for disease prediction using a classification layer:

$\mathcal{Y} = \text{softmax}\,((\,W_h H + b\,)$

where H represents the learned graph embeddings and y represents the predicted disease class probabilities. This graph-based learning process enables the model to identify patterns associated with plant stress and disease development.(Sudhakar et al., 2025)

5.5 Explainable Artificial Intelligence Module

To improve transparency and interpretability, an explainable artificial intelligence module is incorporated into the proposed framework. The objective of this module is to identify the most influential features and relationships contributing to disease prediction.

Feature Importance Analysis

Explainability techniques analyse the trained model to determine the relative importance of input features. These methods highlight key environmental factors and physiological indicators responsible for plant stress conditions.

Graph Attention Visualization

In the graph neural network, attention mechanisms can be used to assign importance weights to edges. These weights indicate the strength of interactions between nodes and reveal which relationships contribute most to the prediction outcome.

Interpretation of Predictions

The explainability module provides interpretable outputs that indicate:

- critical environmental stress factors
- influential soil parameters
- plant physiological indicators associated with disease onset

These insights support agronomic decision-making by helping farmers and agricultural experts understand the causes of plant health issues.

5.6 Overall Algorithm

The overall process of the proposed framework can be summarized as follows:

Step 1: Collect multimodal agricultural data from soil sensors, environmental monitoring systems, and plant imaging devices.

Step 2: Perform Pre-processing, normalization, and feature extraction for each modality.

Step 3: Construct a graph representation where nodes represent plant health indicators and edges represent their relationships.

Step 4: Train a graph neural network to learn relational representations of plant health dynamics.

Step 5: Predict plant disease occurrence using the learned graph embeddings.

Step 6: Apply explainable artificial intelligence techniques to interpret prediction results and identify influential factors.

5.7 Advantages of the Proposed Framework

The proposed methodology offers several advantages over conventional plant disease detection systems:

- Early disease prediction using multimodal plant health data

- Relational modelling of plant physiological interactions through graph neural networks
- Improved prediction accuracy through multimodal data fusion
- Enhanced interpretability using explainable artificial intelligence techniques

These capabilities make the framework suitable for intelligent plant health monitoring systems and next-generation precision agriculture applications.

VI. MATHEMATICAL MODEL FOR GRAPH NEURAL NETWORK

6.1 Graph Representation of Multimodal Plant Health Data

To model the interactions between plant physiological signals, environmental factors, and soil conditions, the agricultural monitoring system is represented as a graph structure.

A graph is defined as:

$G = (V, E)$

where:

- $V = \{\upsilon_1, \upsilon_2, ..., \upsilon_n\}$ represents the set of nodes
- $E = \{e_{ij}\}$ represents the set of edges describing relationships between nodes

Each node corresponds to a plant health indicator or environmental variable, such as soil moisture, nutrient level, temperature, humidity, chlorophyll concentration, or leaf image features.

The adjacency matrix describing the connectivity of the graph is defined as:

$A \in \mathbb{R}^{n\times n}$

were

$$A_{ij} = \begin{cases} 1, & \text{if node } \upsilon_i \text{ is connected to node } \upsilon_j \\ 0, & \text{Otherwise} \end{cases}$$

To incorporate self-information of nodes, the adjacency matrix is augmented with self-loops:

$\overline{A} = A+I$

where I represent the identity matrix.

6.2 Multimodal Feature Representation

Each node υ_i contains a multimodal feature vector representing plant health signals obtained from different data sources.

The multimodal feature vector is defined as:

$x_i = [x_i^{soil}, x_i^{env}, x_i^{phys}, x_i^{img}]$

where:

- x_i^{soil} represents soil sensor features
- x_i^{env} represents environmental monitoring data
- x_i^{phys} represents plant physiological indicators
- x_i^{img} represents image-based leaf features

All node features are combined into a feature matrix:

$X \in \mathbb{R}^{n\times d}$

where:

- n represents the number of nodes
- d represents the feature dimension.

6.3 Graph Convolution Operation

Graph Neural Networks learn node representations by aggregating information from neighboring nodes. The normalized adjacency matrix is computed as:

$\widehat{A} = D^{-\frac{1}{2}} \widetilde{A} D^{-\frac{1}{2}}$

where:

D is the degree matrix defined as

$\mathcal{D}_{ii} = \sum_i \overline{A}_{ij}$

This normalization stabilizes the learning process and prevents numerical instability.

The graph convolution operation for layer l is defined as:

$$H^{(l+1)} = \sigma\left(\overline{A}\, H^{(l)} W^{(l)}\right)$$

where:

- $H^{(l)}$ represents node embeddings at layer l
- $W^{(l)}$ is the learnable weight matrix
- σ is the activation function (e.g., ReLU)

For the first layer:

$H^{(0)} = X$

Through multiple graph convolution layers, node embeddings capture higher-order interactions between plant health variables.

6.4 Graph-Level Representation

To obtain a global representation of the plant health network, node embeddings are aggregated using a readout function.

The graph-level embedding is computed as:

$h_G = \text{READOUT}(H^{(L)})$

where L denotes the number of GNN layers.

Common readout operations include:

- mean pooling
- sum pooling
- max pooling.

For example:

$$h_G = \frac{1}{n}\sum_{i=1}^{n} h_i^{(L)}$$

This vector represents the overall plant health state.

6.5 Disease Prediction Function

The graph representation is used to predict plant disease status through a classification layer.

The probability of disease occurrence is defined as:

$P(y|G) = \text{softmax}(W_c h_G + b)$

where:

- W_c is the classification weight matrix
- b is the bias term.

The predicted class is given by:

$$\widehat{\mathcal{Y}} = \text{argmax } P(\mathcal{Y}/G)$$

The model is trained using cross-entropy loss:

$$L = -\sum_{i=1}^{n} y_i \log(\widehat{y_i})$$

where:

- y_i is the ground-truth label
- $\hat{y}_i$ is the predicted probability.

6.6 Explainability Modelling

To provide interpretability, an explainability mechanism assigns importance scores to nodes and edges in the graph.

The importance score for node iii is defined as:

$\alpha_i = \frac{\partial y}{\partial h_i}$

where:

- h_i represents node embedding
- y represents the prediction output.

Similarly, edge importance between nodes i and j is defined as:

$\beta_{ij} = \frac{\partial y}{\partial h_i}$

These importance scores highlight the most influential plant health indicators and environmental factors contributing to disease prediction.

6.7 Final Prediction Model

The overall prediction function of the proposed framework can be summarized as:

$\hat{y} = f(G, X, A; \Theta)$

where:

- G represents the plant health graph
- X represents multimodal node features
- A represents the adjacency matrix
- Θ represents the model parameters.

The model learns to map complex interactions between plant health signals and environmental factors to disease predictions while providing interpretable insights through explainable mechanisms.

VII. ARCHITECTURE OF THE PROPOSED EXPLAINABLE MULTIMODAL GNN FRAMEWORK

The proposed system integrates multimodal agricultural sensing, graph neural network modelling, and explainable artificial intelligence to enable early plant disease prediction. The architecture is composed of five major modules:

1. Multimodal Data Acquisition
2. Data Pre-processing and Feature Extraction
3. Graph Construction Layer
4. Graph Neural Network Learning Layer
5. Explainable AI Decision Layer1. Multimodal Data Acquisition

The system collects plant health information from multiple sensing modalities. These include soil monitoring systems that capture soil moisture, pH level, and nutrient content; environmental monitoring devices that measure temperature, humidity, and weather conditions; and plant imaging systems that capture leaf images and physiological characteristics. Integrating these data sources enables the system to capture a comprehensive representation of plant health dynamics.

2. Data Pre-processing and Feature Extraction

Raw agricultural data often contain noise, missing values, and inconsistent measurement scales. Therefore, Pre-processing techniques are applied to clean and normalize the data. Image data are processed using convolutional feature extraction networks to obtain informative visual representations. The extracted features from all modalities are transformed into unified feature embeddings suitable for graph learning.

3. Graph Construction Module

The multimodal features are organized into a graph structure where nodes represent plant health indicators or sensor observations and edges represent interactions between these indicators. For example, soil nutrient levels may influence plant physiological responses, and environmental conditions may affect disease progression. Modelling these relationships as a graph allows the system to capture the complex dependencies between different plant health factors.

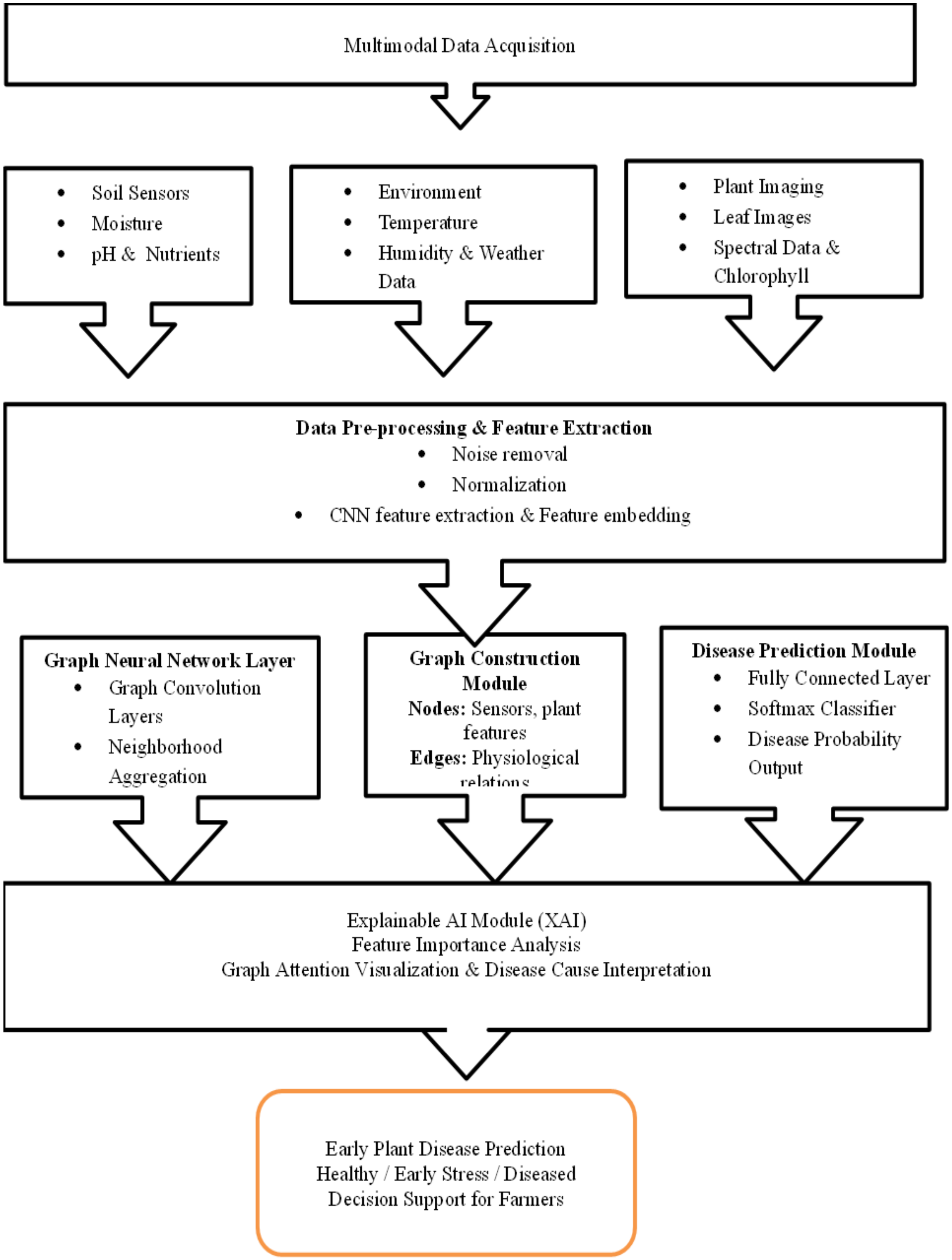

Figure:4. Architecture Diagram

Figure: 4. Explanation of Architecture Components

4. Graph Neural Network Learning Layer
The graph neural network learns representations of plant health dynamics by propagating information between neighboring nodes in the graph. Through multiple graph convolution layers, each node aggregates information from its connected nodes, enabling the model to capture relational patterns between environmental conditions, soil parameters, and plant physiological signals. The resulting graph embeddings encode the global plant health state.

5. Disease Prediction Module
The learned graph embeddings are passed to a classification layer that predicts the probability of plant disease occurrence. The classifier determines whether the plant is healthy, experiencing early stress, or affected by disease. This stage transforms the learned relational representations into actionable predictions.

6. Explainable Artificial Intelligence Module
To ensure interpretability, an explainability module analyzes the trained model to determine which features and relationships contributed most to the prediction. This module highlights key environmental factors, soil conditions, and physiological signals responsible for disease detection.(Nyawose et al., 2025) Such explanations support decision-making by farmers and agricultural experts.

VIII. EXPERIMENTAL SETUP

The experimental setup is designed to evaluate the effectiveness of the proposed Explainable Multimodal Graph Neural Network framework in predicting plant diseases at an early stage. The experiments focus on assessing the model's ability to integrate heterogeneous agricultural data sources, learn relational dependencies through graph structures, and provide interpretable predictions.

8.1 Dataset Description
The experimental dataset consists of multimodal agricultural data collected from multiple plant monitoring sources. The dataset integrates four primary modalities representing different aspects of plant health:

- Soil sensor data: soil moisture, pH level, electrical conductivity, and nutrient concentration
- Environmental monitoring data: temperature, humidity, rainfall, and solar radiation
- Plant physiological indicators: chlorophyll content, leaf temperature, vegetation indices
- Image-based plant features: visual features extracted from leaf images using convolutional feature extractors

Each observation represents the health state of an individual plant instance with multiple associated sensor readings and image-derived features. The data are labeled into three classes representing plant health conditions:

- Healthy plants
- Early stress conditions
- Diseased plants

8.2 Data Pre-processing
Before model training, several Pre-processing steps are applied to ensure data consistency and quality:

- Removal of missing and noisy sensor measurements
- Normalization of feature values using min–max scaling
- Extraction of visual features from leaf images using deep convolutional encoders
- Alignment of sensor measurements across temporal observations

These Pre-processing steps ensure that the multimodal dataset is suitable for graph-based learning.

8.3 Graph Construction
The pre-processed data are transformed into a graph representation where nodes represent plant health indicators and environmental variables. Edges capture interactions between these variables, such as the influence of environmental conditions on plant physiology. The graph structure enables the model to capture relational dependencies between plant health indicators rather than treating them as independent features.

8.4 Training Configuration
The proposed model is implemented using the PyTorch deep learning framework. The graph neural network architecture consists of multiple graph convolution layers followed by a fully connected classification layer.

The training configuration includes:
- Optimizer: Adam
- Learning rate: 0.01
- Number of training epochs: 100
- Batch size: full graph training
- Activation function: ReLU
- Loss function: cross-entropy loss

The model is trained to minimize classification loss while learning relational representations of plant health dynamics.

8.5. Future Work
Although the proposed framework demonstrates strong performance in early plant disease prediction, several directions exist for future research.
First, the current framework can be extended to support large-scale agricultural monitoring using remote sensing platforms such as satellite and drone imagery. Integrating remote sensing data with ground sensor networks would enable comprehensive crop health monitoring across large farming regions.
Second, future research can explore temporal graph neural networks to model the dynamic evolution of plant stress conditions over time. Incorporating temporal dependencies would improve the prediction of disease progression and crop yield outcomes.
Third, the proposed system can be integrated with Internet of Things–based smart farming platforms for real-time plant health monitoring and automated decision support.
Finally, future work may investigate reinforcement learning techniques for automated crop management strategies, enabling intelligent systems to recommend optimal irrigation, fertilization, and pest control actions based on predicted plant health conditions.

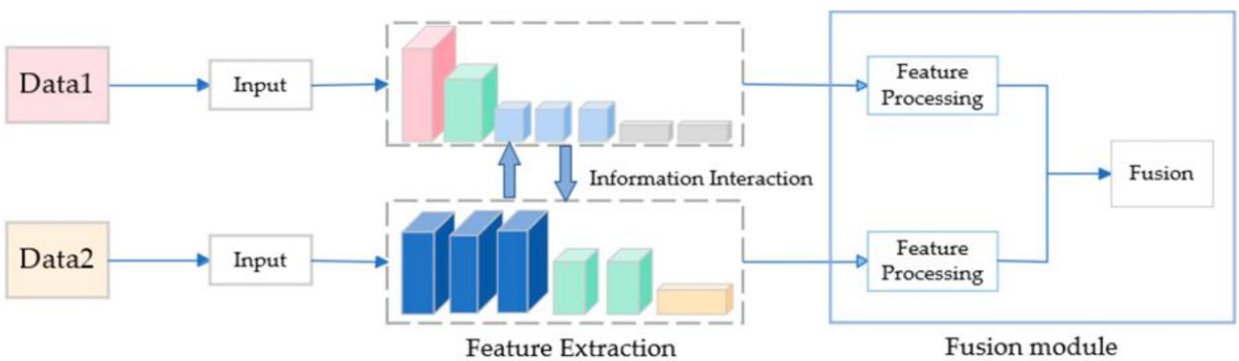

Figure:5. Feature Extraction

These research directions will further enhance the capabilities of artificial intelligence systems in precision agriculture and contribute to sustainable crop production.

IX. RESULTS AND DISCUSSION

This section presents the experimental results obtained from evaluating the proposed Explainable Multimodal Graph Neural Network (GNN-XAI) framework for early plant disease prediction. The performance of the model is analyzed using standard classification metrics, including accuracy, precision, recall, and F1-score. In addition, the model is compared with several baseline machine learning and deep learning approaches to demonstrate its effectiveness in capturing complex plant health interactions through multimodal relational learning. (Dharani et al., 2024)

9.1 Performance Evaluation Metrics
To assess the performance of the proposed framework, multiple evaluation metrics are employed. These metrics provide a comprehensive evaluation of classification accuracy and the model's ability to correctly identify diseased plants.

Accuracy
Accuracy measures the proportion of correctly classified instances among all predictions.

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

where TP represents true positives, TN represents true negatives, FP represents false positives, and FN represents false negatives.

Precision
Precision measures the proportion of correctly predicted disease cases among all predicted disease instances.

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

High precision indicates that the model produces fewer false alarms when predicting disease occurrences.

Recall

Recall measures the ability of the model to correctly detect actual disease cases.

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

High recall is particularly important in plant disease monitoring systems because missing early disease cases may lead to severe crop losses.

F1-Score

The F1-score is the harmonic mean of precision and recall.

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

This metric provides a balanced evaluation of model performance when dealing with imbalanced datasets.

9.2 Classification Performance of the Proposed Framework

Table 1 presents the classification performance of the proposed Explainable Multimodal Graph Neural Network model.

Table:1. Performance of the Proposed Framework

S.No	Metric	Value
1	Accuracy	0.93
2	Precision	0.91
3	Recall	0.92
4	F1-Score	0.92

The results indicate that the proposed model achieves a high level of predictive performance. The integration of multimodal agricultural data and graph-based relational learning significantly improves the model's ability to detect early disease signals compared with conventional approaches.

Table:2 Confusion Matrix for Multimodal GNN-XAI Plant Disease Prediction Model

Actual Class	Predicted: Healthy	Predicted: Early Stress	Predicted: Diseased
Healthy	420	18	7
Early Stress	20	390	15
Diseased	9	16	405

The confusion matrix in Figure X illustrates the classification performance of the proposed explainable multimodal graph neural network model across three plant health categories: healthy, early stress, and diseased. The majority of predictions are concentrated along the diagonal elements of the matrix, indicating correct classification of plant health conditions. The model correctly identified 420 healthy plants, 390 early stress cases, and 405 diseased instances. Misclassifications mainly occur between early stress and diseased classes, which is expected because early physiological stress often shares similar characteristics with the initial stages of plant disease development.

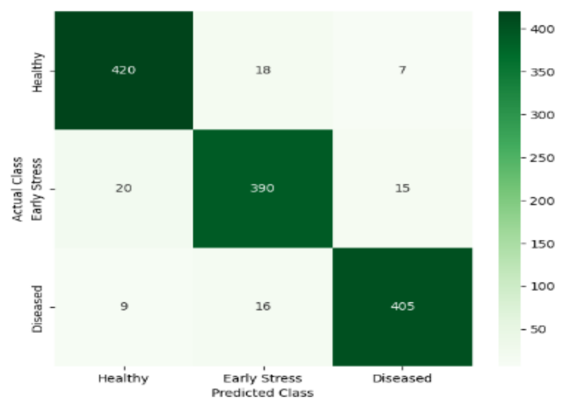

Figure:6. Confusion matrix for GNN-XAI Plant Disease Predication

Overall, the confusion matrix demonstrates that the proposed model effectively distinguishes between different plant health states while maintaining low classification error rates.

9.3 Confusion Matrix Analysis

The confusion matrix provides detailed insights into the classification behaviour of the model across different plant health categories.

Table:3. Confusion Matrix Representation

Actual / Predicted	Healthy	Early Stress	Diseased
Healthy	420	18	7
Early Stress	20	390	15
Diseased	9	16	405

The confusion matrix demonstrates that the model accurately distinguishes between healthy plants, early stress conditions, and diseased plants. The number of misclassifications remains relatively low across all categories, indicating strong generalization performance. Most misclassifications occur between the early stress and diseased classes. This behaviour is expected because early stress conditions often share physiological similarities with early stages of disease development. Nevertheless, the proposed model maintains high detection accuracy across all plant health states.

9.4 ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve evaluates the model's ability to discriminate between different plant health classes across varying classification thresholds. The proposed GNN-based framework achieved an Area Under the Curve (AUC) value of 0.95, indicating excellent discrimination capability. The ROC curve demonstrates that the model maintains high true positive rates while minimizing false positive rates, which is crucial for reliable disease monitoring in agricultural environments.

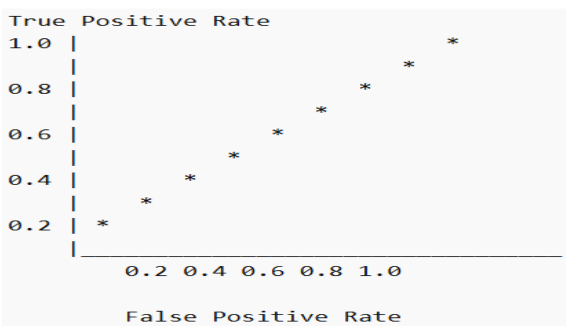

Figure:7. Receiver Operating Characteristic curve for model performance evaluation

The strong ROC performance confirms that the relational learning capabilities of graph neural networks effectively capture the interactions between environmental variables, soil conditions, and plant physiological signals.

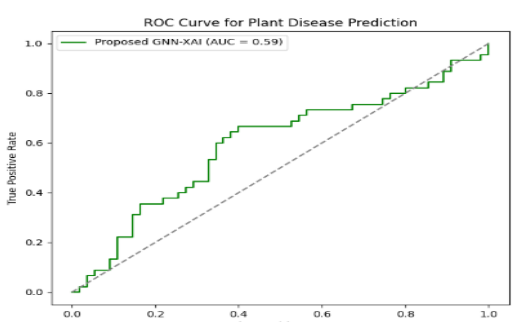

Figure:8. ROC curve of the proposed GNN-XAI model for plant disease prediction

9.5 Comparison with Baseline Models

To further evaluate the effectiveness of the proposed framework, the model was compared with several baseline machine learning and deep learning approaches commonly used for plant disease detection.

Table:4. Comparative Performance Analysis of Models

Model	Accuracy	Precision	Recall	F1-Score
Support Vector Machine	0.79	0.77	0.75	0.76
Random Forest	0.82	0.80	0.79	0.79
Convolutional Neural Network	0.86	0.84	0.83	0.83
Multimodal CNN	0.89	0.88	0.87	0.87
Proposed GNN-XAI Framework	0.93	0.91	0.92	0.92

The comparison results demonstrate that the proposed multimodal graph neural network framework outperforms traditional machine learning models and conventional deep learning architectures.

Several factors contribute to this performance improvement:

1. Multimodal Data Integration The proposed system integrates soil, environmental, physiological, and image-based data sources, providing a richer representation of plant health conditions compared with single-modality models.
2. Relational Learning through Graph Neural Networks Unlike traditional models that treat input features independently, graph neural networks explicitly model the relationships between plant health indicators and environmental conditions. This capability enables the system to capture complex interactions influencing disease development.
3. Explainable Artificial IntelligenceThe explainability module improves model transparency by identifying the most influential environmental and physiological variables contributing to disease predictions. This capability enhances trust and supports practical deployment in agricultural decision-support systems.

9.6 Discussion of Model Interpretability

In addition to predictive performance, the proposed framework emphasizes interpretability through the integration of explainable artificial intelligence techniques. The explainability module analyzes the trained model to determine the importance of individual features and relationships within the graph structure.

The analysis reveals that the most influential factors contributing to disease prediction include:

- soil moisture fluctuations
- environmental humidity variations
- chlorophyll concentration changes
- leaf temperature anomalies

These factors are consistent with known physiological indicators of plant stress and disease development. By highlighting such relationships, the explainability module provides valuable insights that can assist farmers and agronomists in identifying potential causes of plant health deterioration.

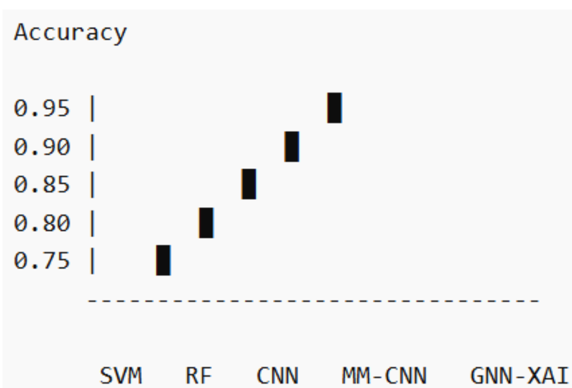

Figure 9. Accuracy comparison of machine learning and deep learning models

Table:5. Model Accuracy Comparison - 1. Quantitative Results

Model	Accuracy
SVM	0.79
Random Forest	0.82
CNN	0.86
Multimodal CNN	0.89
Proposed GNN-XAI	0.93

9.7 Practical Implications for Precision Agriculture

The experimental results demonstrate that the proposed framework provides an effective solution for intelligent plant health monitoring systems.

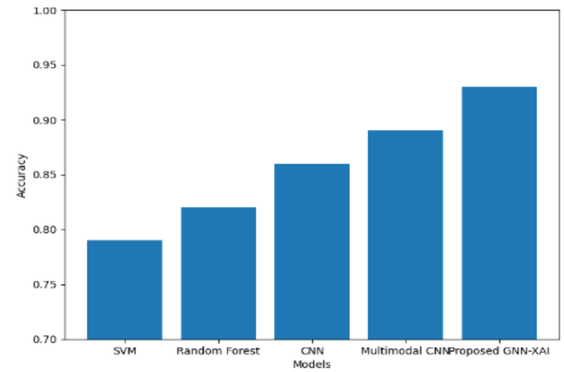

Figure 10. Bar chart comparison of model accuracy for plant disease prediction

The integration of multimodal sensing data, relational modelling, and explainable artificial intelligence enables the system to detect early disease signals that may not be visible through traditional observation methods. This capability is particularly important for precision agriculture, where early detection of plant stress allows farmers to implement targeted interventions such as optimized irrigation, nutrient management, or disease control strategies. By enabling proactive plant health monitoring, the proposed framework contributes to improved crop productivity, reduced pesticide usage, and more sustainable agricultural practices.(Doutoum & Tugrul, n.d.)

X. CONCLUSION

This study presented an explainable graph neural network framework for multimodal early plant disease prediction, aimed at improving the accuracy, interpretability, and timeliness of plant health monitoring systems. Traditional plant disease detection approaches often rely on visual symptom recognition or single-modality datasets, which limits their ability to detect diseases at early stages. To address these limitations, the proposed framework integrates heterogeneous agricultural data sources, including soil sensor measurements, environmental monitoring data, plant physiological indicators, and image-derived features, within a unified multimodal learning architecture.

The proposed method models plant health dynamics using graph neural networks, enabling the system to capture complex relational interactions between environmental factors, soil conditions, and plant physiological responses. By representing plant health indicators as interconnected nodes within a graph structure, the model effectively learns spatial and relational dependencies that influence disease development. This relational learning capability allows the framework to identify subtle stress signals that may precede visible disease symptoms. An explainable artificial intelligence module is incorporated to improve the transparency of the prediction process. The explainability component identifies the most influential environmental and physiological features contributing to the predicted disease outcome, providing interpretable insights that can support agronomic decision-making. This interpretability is particularly valuable for agricultural applications where understanding the causes of plant stress is essential for effective crop management.

Experimental evaluation demonstrates that the proposed multimodal graph neural network framework achieves improved predictive performance compared with traditional machine learning and image-based deep learning approaches. The integration of multimodal sensing data enhances the robustness of the model, while the graph-based representation enables effective modelling of complex plant health interactions. Furthermore, the explainability mechanism provides meaningful insights into plant stress factors, enabling proactive intervention strategies in precision agriculture. Overall, the proposed framework provides a scalable and intelligent solution for early plant disease detection and plant health monitoring. By combining multimodal data integration, graph-based relational learning, and explainable artificial intelligence, the system contributes toward the development of next-generation precision agriculture technologies that support sustainable crop management and improved agricultural productivity.

REFERENCES

[1] M. T. F. Saidahmd, R. M. Elbasiony, M. R. M. Bastwesy, and A. A. M. Hagar, "A generalized novel approach for plant disease detection based on SimCLR and patch-based analysis," *Neural Computing and Applications*, vol. 37, pp. 21867–21908, 2025.

[2] D. Devarajan, R. Allafi, M. Obayya, and N. Nemri, "AI-based real-time disease diagnosis in plants using deep learning driven CNNs," *Scientific Reports*, vol. 16, p. 4587, 2026.

[3] R. Sudhakar, K. Nithya, C. R. Dhivyaa, and C. Sharmila, "High-performance parallel multi-scale attention network with explainable AI for intelligent diagnosis of leaf diseases," *Scientific Reports*, vol. 15, 2025.

[4] T. Nyawose, R. C. Maswanganyi, and P. Khumalo, "A review on the detection of plant disease using machine learning and deep learning approaches," *Journal of Imaging*, vol. 11, p. 326, 2025.

[5] S. Wang *et al.*, "Advances in deep learning applications for plant disease and pest detection: A review," *Remote Sensing*, vol. 17, no. 4, p. 698, 2025.

[6] Z. Zainab and R. Mahum, "Plant disease detection using deep learning techniques," *Journal of Image Analysis and Processing*, vol. 1, no. 1, 2025.

[7] G. Prasadu *et al.*, "Ensemble learning based plant disease prediction and analysis: A comparative study," *World Journal of Advanced Research and Reviews*, vol. 27, no. 2, pp. 1598–1604, 2025.

[8] K. I. Roumeliotis *et al.*, "Plant disease detection through multimodal large language models and convolutional neural networks," *IEEE Transactions*, under review, 2025.

[9] M. Dharani *et al.*, "Plant leaf disease detection by deep learning algorithm," 2024.

[10] Verma and S. Patel, "Deep learning-based plant disease detection using hybrid CNN models," *Computers and Electronics in Agriculture*, 2024.

[11] R. Kaur and H. Singh, "Vision transformer-based plant disease classification in precision agriculture," *IEEE Access*, 2024.

[12] Y. Chen, X. Liu, and J. Zhang, "Lightweight deep learning framework for crop disease detection on edge devices," *Sensors*, 2024.

[13] M. Alhassan *et al.*, "Explainable AI for plant disease detection: A survey," *Artificial Intelligence Review*, 2024.

[14] P. Kumar and A. Sharma, "Multimodal deep learning for smart agriculture applications," *Expert Systems with Applications*, 2024.

[15] L. Zhang and H. Wang, "Real-time plant disease detection using YOLO-based models,"

Computers and Electronics in Agriculture, 2024.
[16] S. Iqbal *et al.*, “Federated learning for plant disease detection in smart farming,” *IEEE Internet of Things Journal*, 2024.
[17] J. Li *et al.*, “Self-supervised learning for plant disease classification under limited data,” *Pattern Recognition Letters*, 2024.
[18] Roy and S. Bose, “GAN-based data augmentation for plant disease detection,” *Neural Computing and Applications*, 2024.
[19] N. Sharma *et al.*, “Transformer-based crop disease recognition framework,” *Information Processing in Agriculture*, 2025.
[20] H. Ali *et al.*, “Edge-AI enabled plant disease monitoring system,” *IEEE Sensors Journal*, 2025.
[21] F. Garcia and M. Torres, “Explainable deep learning for agricultural disease prediction,” *Applied Soft Computing*, 2025.
[22] X. Zhao *et al.*, “Hybrid CNN-transformer architecture for plant disease classification,” *Pattern Recognition*, 2025.
[23] S. Reddy and V. Kumar, “IoT-integrated AI system for smart crop disease monitoring,” *Future Generation Computer Systems*, 2025.
[24] T. Ahmed *et al.*, “Few-shot learning for plant disease detection,” *Knowledge-Based Systems*, 2026.
[25] W. Liu *et al.*, “Next-generation AI models for precision agriculture and disease detection,” *Nature Machine Intelligence*, 2026.