RESEARCH PAPER

The Significance of Hybrid CNN and ANN Model in Design and Implementation of Deep Learning Model for Plant Disease Detection

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ABSTRACT

Plant disease is a serious threat to agricultural productivity and food security worldwide. Traditional diagnostic methods such as manual observation and laboratory testing are time-consuming, labor-intensive and error prone. The emergence of artificial intelligence (AI) and deep learning (DL) offer scalable solutions for precision agriculture in plant disease detection using advanced computational techniques to process large datasets. Hybrid deep learning architecture integrates Convolutional Neural Networks (CNNs) along with Artificial Neural Networks (ANNs) can leverage both visual and contextual data to improve detection performance. The hybrid CNN-ANN model was developed to analyze visual data (plant images) and contextual data (environmental and soil metrics). The CNN module extracted spatial and textural features from plant images, while the ANN module processed environmental parameters. These outputs were fused into a unified feature vector for disease classification. A total of 15 plant species and their associated diseases were analyzed using 200-270 training samples and 150-190 testing samples for each disease across a total of 1000 images. The model was judged by metrics such as detection accuracy, AUC, sensitivity etc. Data augmentation, pre-trained architectures (e.g., ResNet50) and early stopping techniques were utilized to improvise model performance. The hybrid model saliently achieved detection accuracy consistently above 87% with majority of diseases surpassing 90%. High-performing cases like Rice Blast (92.5%), Tomato Early Blight (93.8%), and Coffee Rust (93.0%), with AUC values of 0.93 or higher, sensitivity exceeding 94% and specifically above 90%. Diseases of Sugarcane Red Rot and Tea Blister Blight exhibited sensitivities of 92.4% and 92.1% and specificities of 91.1% and 90.5% respectively. Moderate accuracy for Coconut Bud Rot (87.5%) and Mustard Alternaria Blight (87.8%) was due to smaller training sample sizes.

Keywords: *Convolutional Neural Network, Artificial Neural Network, Deep Learning, Plant Disease, Accuracy, Sensitivity, Precision agriculture.*

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INTRODUCTION

Agriculture sector is key in sustaining the global economy and ensuring food security. It also plays a crucial role in providing ecosystem services and helps mitigate climate change through carbon sequestration (1). However, plant and crop diseases pose a challenge to crops yield and quality, directly impacting agricultural productivity and farmers' livelihoods (2–4). Timely diagnosis of plant diseases are imperative to mitigate these effects and implement effective solutions. Traditionally, manual observation and laboratory testing are often time-consuming, labor-intensive and susceptible to human error (5,6,7). In this context, advancements in AI and DL have opened new avenues for handling these challenges efficiently(8).

Deep learning, particularly CNNs and ANNs, have emerged as a technological diagnostic approach for plant disease detection. CNNs are well-suited for image-based tasks to capture spatial hierarchies in visual data (9,10). ANNs provide a foundation for understanding patterns and relationships within diverse datasets leading to flexible and scalable models for identifying plant diseases with high accuracy (11,12,13).

This paper investigates the significance of CNN and ANN architectures in design and implementation of deep learning models for diagnosing plant disease. It explores their fundamental principles, comparative advantages and practical applications and addresses challenges and potential future developments in the field (14,15,16,17).

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BACKGROUND AND MOTIVATION

Plant disease detection has historically been of paramount importance to agriculture, serving as a critical factor in ensuring food security for sustainable farming practices. Plant diseases could result in destroying crop yields causing financial losses and risking global food supply if they are unidentified or untreated. Conventional methods of plant disease detection were laborious, tedious and prone to human error. Furthermore, these lines of action were post-action, frequently detecting diseases only after they reached an advanced stage thereby limiting the application of subsequent interventions.

In recent years, AI and DL technologies offer effective automated solutions to the challenges faced in traditional plant disease diagnostics. By using large datasets and advanced computational techniques these technologies are evolving models which detect diseases related to flora efficiently. CNNs have revolutionized image-based diagnostics by extracting and analyzing intricate visual patterns from plant images. ANNs have also facilitated the integration and analysis of diverse datasets that include environmental factors, soil properties and other non-visual parameters. These methodologies have shifted plant disease detection from a labor-intensive process to a scalable and automated system - with the potential to greatly enhance decision- making in modern agriculture.

Overview of CNN and ANN

Fundamentals of CNNs: CNNs have emerged as a key milestone in the field of deep learning in tasks involving image processing and computer vision. CNNs are designed to emulate the hierarchical structure of the human visual system which make them highly accurate and skilled at extracting spatial features and patterns from image data. This capability is critical for applications such as plant disease detection. Subtle visual differences in leaf color, texture or shape may indicate the presence of disease (18).

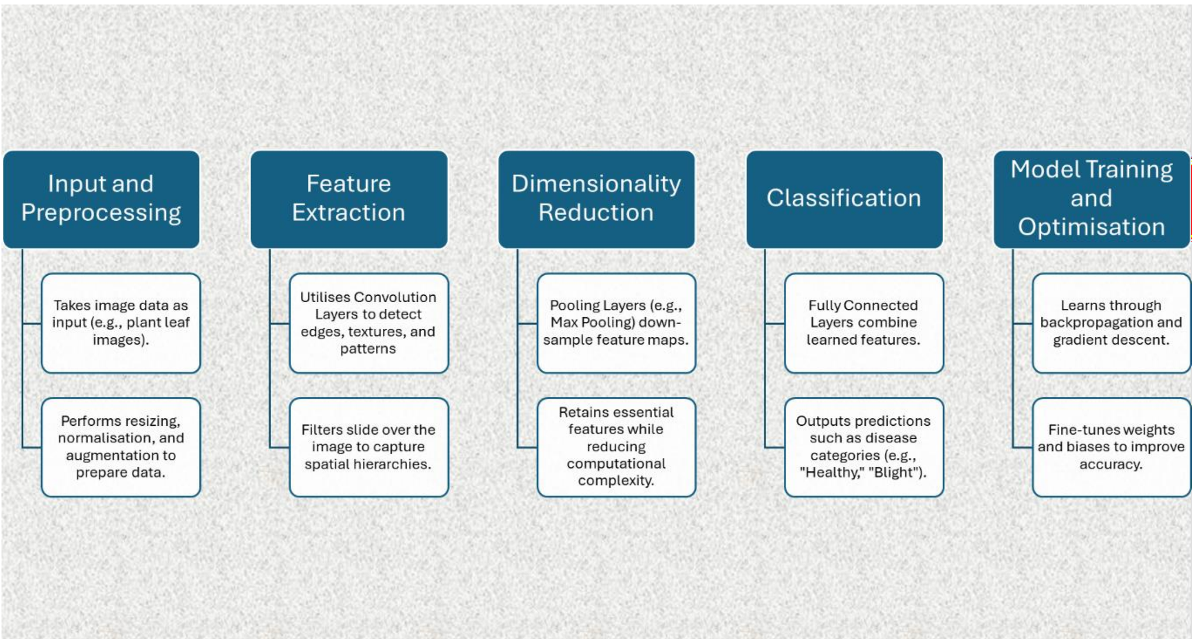


Figure 1. Conceptual architecture of a convolutional neural network (CNN), highlighting key operations including convolutional feature extraction, pooling-based dimensionality reduction, fully connected classification, and training via backpropagation.

At the core of a CNN there is layered architecture and specialized operations within each layer. The convolutional layer is the hallmark of CNNs, and it applies a set of learnable kernels to the input image. These filters slide across the image to capture local patterns such as edges, corners or textures. This operation preserves spatial relationships for the model to learn essential features specific to plant disease symptoms. Multiple filters allow the extraction of diverse features at varying levels of granularity (19,20,21,22).

Following the convolutional layer there is pooling layer introduced to reduce spatial dimensions of feature maps. This down-sampling process retains significant features while reducing computational complexity and overfitting risks. Common pooling methods such as max pooling and average pooling ensure that the network focuses on the most prominent patterns.

To introduce non-linearity and enhance the model's learning ability in complex relationships, activation functions are applied after the convolutional operations. The rectified linear unit (ReLU) is used in CNNs, as it effectively addresses issues of vanishing gradients while maintaining computational efficiency. This activation function enables the network to model non-linear dependencies for distinguishing between healthy and diseased plants (23,24).

The fully connected layers serve as the final stage in a CNN - where the high-level features extraction from the earlier layers are combined to perform classification or regression tasks (25,26). These layers map the extracted features to specific outputs - identifying the type of plant disease present. Every neuron in one layer is connected to every neuron in the next layer. The fully connected layers synthesize the learned information to provide accurate predictions as depicted in the figure below.

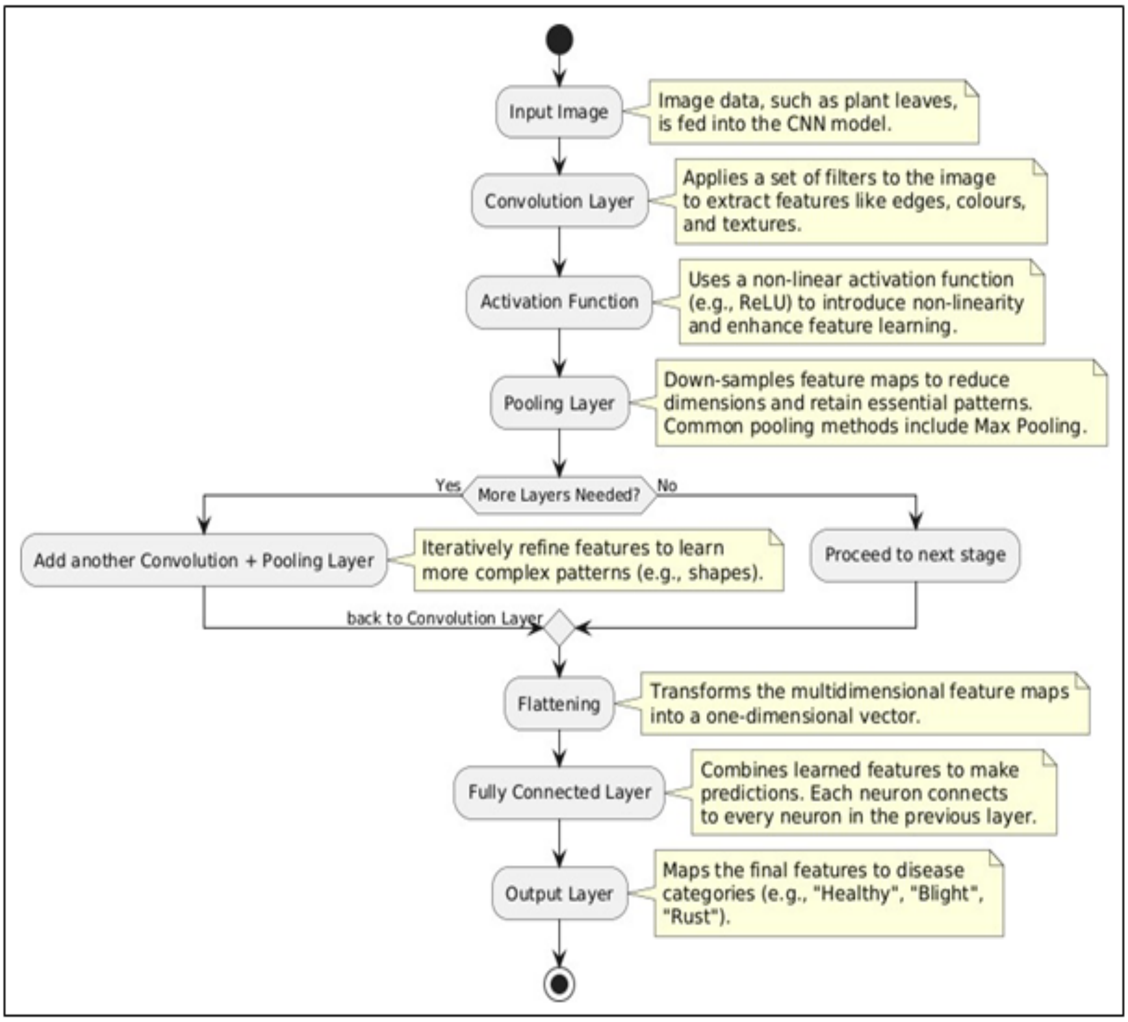


Figure 2: Figure 2. Schematic flowchart of a convolutional neural network (CNN) pipeline showing the progression from input data through convolution, nonlinear activation, pooling-based dimensionality reduction, iterative feature extraction via stacked layers, flattening, and fully connected classification to the final output.

CNNs have demonstrated good proficiency in analyzing plant images for disease detection. Their ability to automate and learn hierarchical feature representations hasdrastically reducedtheir dependence on manual feature engineering which in turn has enabled faster and more accurate diagnostic processes.

Fundamentals of ANNs: ANNs are foundation elements in the domain of machine learning (ML), inspired by the structure and functioning of biological neural networks. ANNs are designed to recognize and learn patterns within data by mimicking the way the human brain processes information. Their versatility and adaptability make them highly suitable for tasks involving classification, prediction and pattern recognition, including applications in agriculture such as plant disease detection (12,13,27).

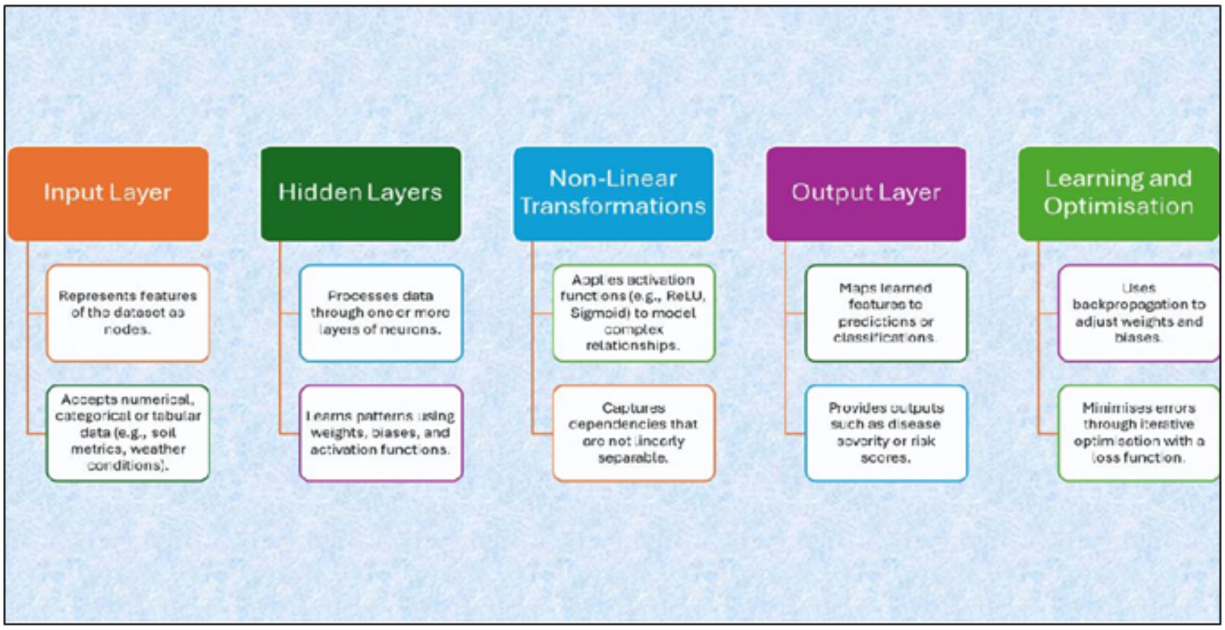


Figure 3: Conceptual diagram of an artificial neural network (ANN) showing the flow of data from the input layer through hidden layers with nonlinear transformations to the output layer, along with model training using backpropagation and optimization techniques.

Structure and Functioning: The structure of an ANN is composed of three primary types of layers: the input layer, hidden layers, and the output layer. The input layerserves as the gateway for data to enter the network wherein each input node corresponds to a specific feature of the dataset.(28,29) This layer ensures that the data is properly structured for subsequent processing as shown in figure below.

The hidden layersconstitute the computational core of the network consist of multiple interconnected nodes or neurons. Each neuron processes the input data by applying a weighted sum and passing it through an activation function(30). These weights and biases are adjusted iteratively during the training process to minimize the error in the model's predictions. The hidden layers enable the network to learn intricate relationships and dependencies within the data. On plant disease detection, hidden layers might learn associations between environmental conditions, plant growth stages and disease symptoms. The output layer provides the final predictions of the network, mapping the learned patterns to specific classes or outputs. For example, in a plant disease classification task, the output layer may assign an input to a category such as "healthy", "leaf spot disease" or "powdery mildew" The functioning of an ANN is driven by the back propagation algorithm, which iteratively updates the weights and biases to optimize the network's performance (31,32,33). During this process, the network calculates the error between its predictions and the actual labels, error is propagated backward through the network to refine the parameters. This learning mechanism improves ANNs accuracy as it gives more exposure to data. The stages involved in ANN are illustrated in figure below:

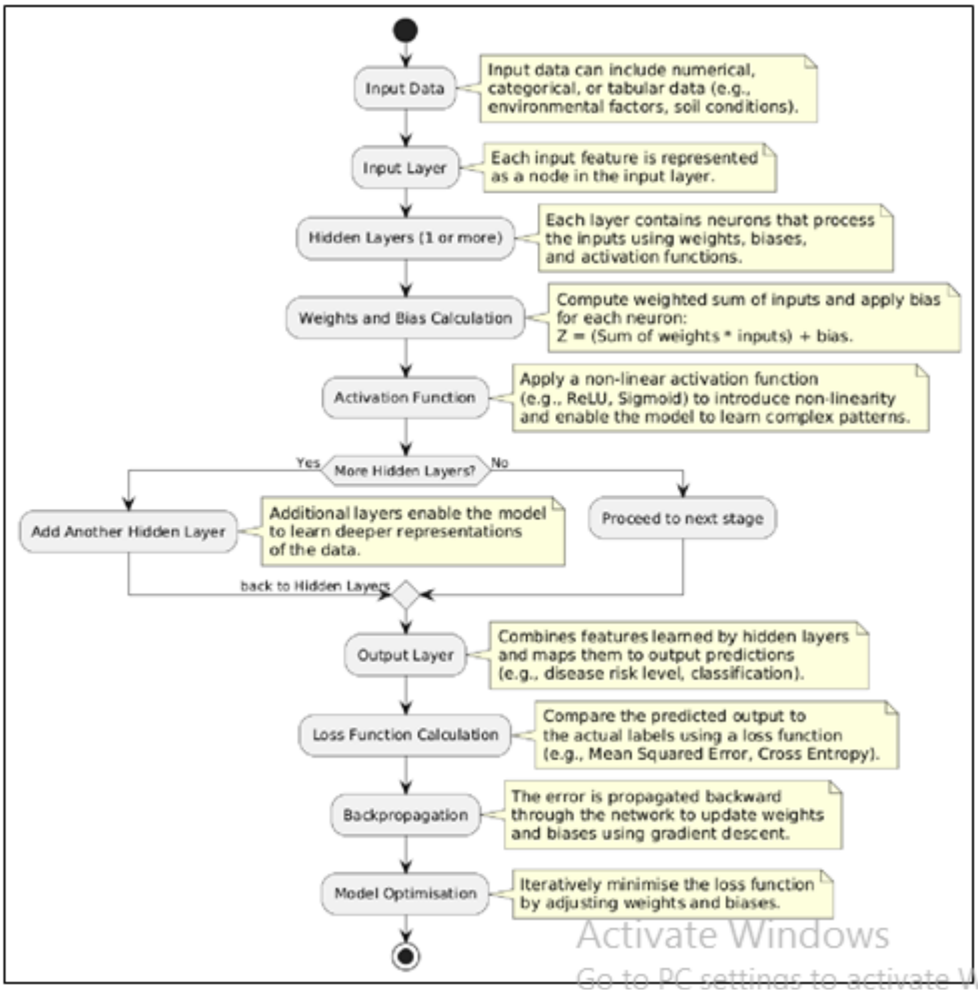


Figure 4: Schematic representation of an Artificial neural network (ANN) showing the flow of data from input through multiple hidden layers with weighted transformations and nonlinear activation functions, leading to output prediction, error evaluation using a loss function, and parameter updates through backpropagation and optimization.

Application in Pattern Recognition and Classification: ANNs excel in pattern recognition and classifications problems which are useful in scenarios where relationships within data are complex or non-linear. For plant disease detection, ANNs can process diverse types of data, including visual features, environmental conditions, and soil properties, to identify correlations indicative of disease presence. In practice, ANNs are often used to complement other methods, such as CNNs, in hybrid architectures. While CNNs are proficient at processing image data, ANNs can incorporate non-visual factors such as humidity, temperature, and soil nutrient levels, creating a more holistic diagnostic model. For instance, an ANN might analyze temporal patterns in sensor data from agricultural fields to predict the likelihood of disease outbreaks under certain environmental conditions (34,35).

Architecture Overview

The proposed hybrid system for plant disease detection integrated the strengths of CNNs and ANNs to provide a comprehensive diagnostic solution as shown in figure below. The architecture used CNNs to extract visual features from plant images and ANNs to process contextual data such as environmental and soil conditions. These outputs were fused to form a unified feature vector which was used for disease classification and risk prediction. This hybrid design ensured accuracy, robustness and adaptability to diverse agricultural scenarios. The architecture consisted of several key layers and modules - each playing role for specific functions that ranged from data acquisition to decision support. We integrated multimodal data to enable iterative learning through user feedback. Using our proposed hybrid CNN-ANN architecture and model, the system was designed to offer practical insights and actionable recommendations for farmers and agricultural professionals.

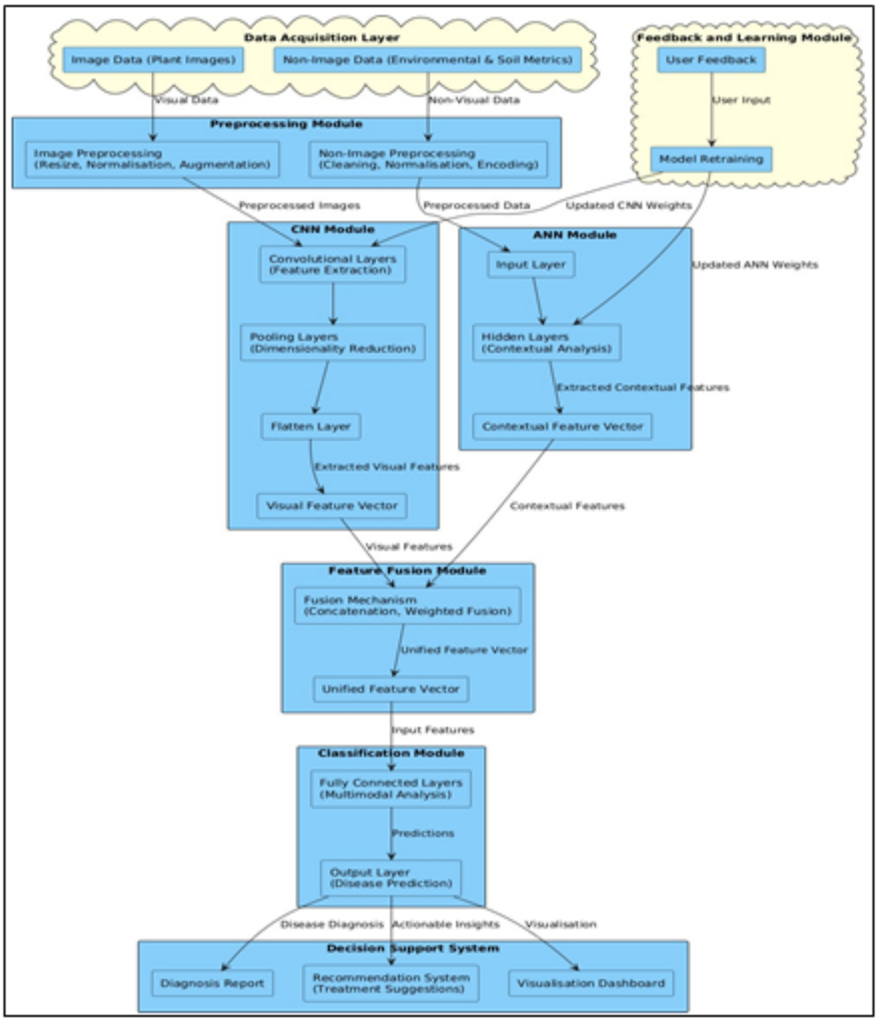


Figure 5: Schematic representation of the proposed multimodal deep learning framework for plant disease prediction, illustrating data acquisition from image and non-image sources, preprocessing, feature extraction using CNN and ANN modules, feature fusion, classification, and feedback-driven model retraining process, along with a decision support system for diagnosis, recommendations, and visualization.

Input and Data Acquisition Layer: The input and data acquisition layer is solely responsible for collecting both visual and non-visual data. Visual Data contains superior quality plant leaves, stems, fruits or other parts. They are generally gathered using mobile devices - cameras, drones and smartphones. Visual data has important data that deals in physical symptoms of plant diseases like discoloration, lesions or any other deformities. Whereas, the non-visual data that summarizes the environment parameters like temperature, humidity, precipitation, soil information - moisture content and soil pH (acidity/alkalinity), is collected using IoT devices and advanced weather monitoring systems. These two data sources make sure that the model can comprehend complete information regarding the plant's condition.

Preprocessing Module: It aims to systematize and process raw input data for further analysis. For visual data preprocessing comprises altering image size to a uniform size, that is in sync with the CNN model, normalization for regularity and noise filtration. To increase the dataset's diversity, augmentation methods like image rotation, horizontal/vertical flipping, and cropping are applied. These transformations help the model learn from varied representations of the data and improve its ability to generalize under different conditions. Non-visual data, here the preprocessing accounts for missing values, normalizing numeric inputs and encoding categorical attributes using techniques like one-hot encoding. This makes the mentioned data clean and structured and in-sync with the ANN module.

CNN Module: The CNN is the central pivot for the processing of visual data. The process begins with convolution layers that filter and find the spatial variables like the edges, textures and patterns that show diseases in plants. Next, the Pooling layers reduce the dimensions of feature maps while not exposing critical data which in turn fine tunes the efficiency. Lastly, a flattening layer transforms the multidimensional feature maps into a one-dimensional vector, making them suitable for further processing. This stage produces a visual feature vector that captures the important disease-related patterns extracted from the plant images

ANN Module: ANN module processes non-visual and contextual data. It takes the input layer that must compute the soil and environment metric like temperature, humidity and soil moisture. The data input variables are further processed in hidden layers where it finds the relations and patterns between the input attributes and potential plant diseases. The outcome of the ANN module is a contextual feature vector that condenses the findings discovered from the non-visual layer. This output complements the visual features extracted by the CNN module creating a broader understanding of the factors influencing plant health.

Feature Fusion Module: This module merges the outputs of the CNN and ANN components into a single, unified feature vector (36,37). This integration is crucial for leveraging the complementary strengths of visual and contextual data. Fusion can be attained by simple unification, where features from both ANN and CNN modules can be merged right away or using weighted fusion that places relative importance to all feature vectors by relative significance in a classification task. The merged feature vector becomes the input for the classification module that shows a deep understanding of the plant's condition.

Classification Module: This module uses fully connected layers to examine the combined feature vector and detect patterns that correspond to plant diseases. This step involves the processing of fused data through a layer of neurons that truly maps the features to pre-defined disease categories. The output layer produces the predictions with probabilities assigned to each category:

- Healthy
- Leaf Spot
- Rust

These probabilities allow the system to show a confidence bar of its predictions that helps in decision making.

Decision Support System: This component provides insights into the model's predictions. It produces a diagnostic report that outlines the detected diseases that are associated with confidence scores and the plant parts that are affected. Further a recommendation system that provides treatment options and preventive measures to each specific disease and environmental conditions. A visualization dashboard is also provided to present diagnostic outcomes, trends and predictions in a clear format, enabling farmers and agricultural experts to make quick and informed decisions.

Feedback and Learning Module: This component supports the continuous enhancement of the system by enabling iterative updates and refinements based on feedback. Users like farmers and agriculture experts can give feedback on the correctness of the predictions and recommendations. The farmer's feedback with the newly gathered data is used to re-train the CNN and ANN models. Back propagation and gradient descent are used to adjust the model's biases and weights that increases the system's performance with time and after a learning curve that are efficient to handle new diseases, crops or any other environmental conditions while retaining its relevance and accuracy.

Sequence Diagram: The sequence diagram represents how the main components of the hybrid CNN–ANN system interacts with each other during the plant disease detection process. It starts by acquiring data, while the farmer and the end-user both give visual data - images and non-visual contextual data - environmental and soil insights. The inputs are then pre-processed to maintain compatibility with the other modules. The CNN module takes the visual features from the images whereas the ANN module must process the contextual insights - (Environmental and soil-related). The generated outcomes of these modules are then merged in a feature fusion module that creates a single feature vector that is used by the classification module to predict the disease and its type. The decision support system provides practical insights, including diagnostic outcomes and suggested treatments, through an interactive dashboard. Additionally, the feedback and learning module enables users to submit feedback, which is then used to continuously refine the model's accuracy and performance, allowing the system to adapt to new data and changing conditions over time as depicted below figure.

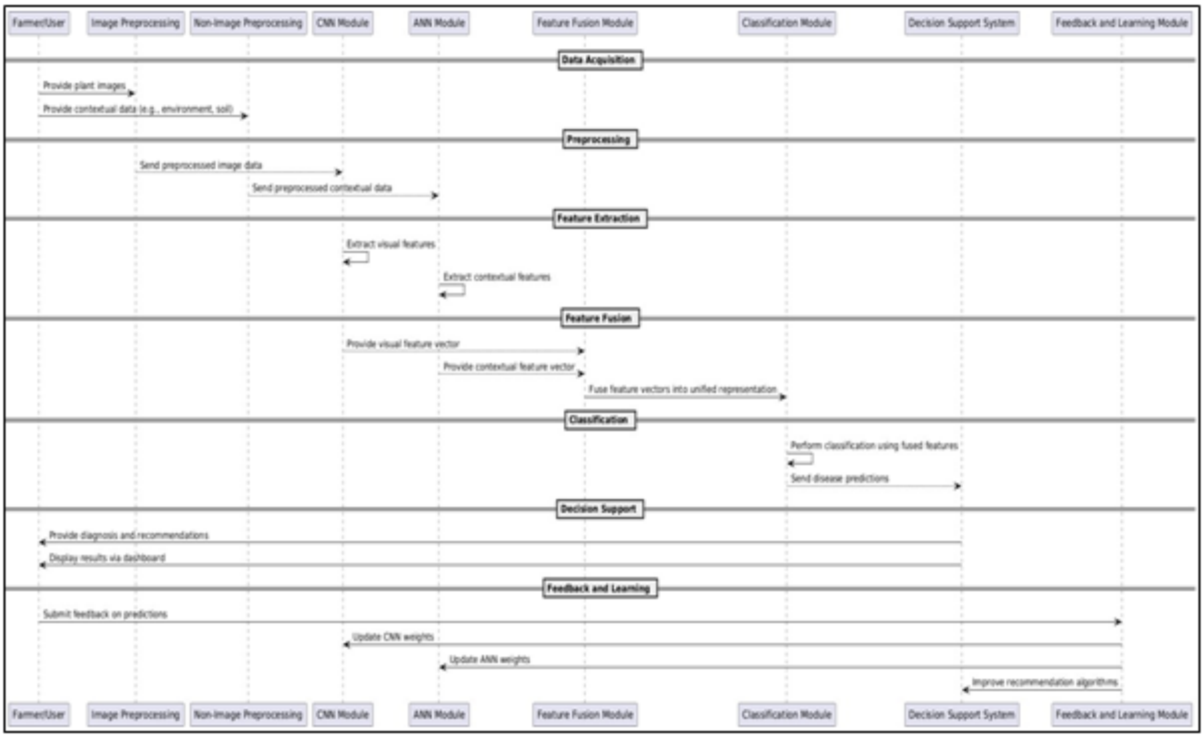


Figure 6 : Sequence diagram representing the workflow of the proposed multimodal framework, showing the flow of image and non-image data from user input through preprocessing, feature extraction using CNN and ANN modules, feature fusion, classification, decision support, and feedback-driven model updates.

MATERIALS AND METHODS

Data Acquisition: In this study, two types of data were collected to facilitate a comprehensive analysis of plant diseases: visual data and contextual data. Visual data comprised high-resolution images of plant leaves affected by diseases that were captured using a standard digital camera. These images were also sourced from open-source existing datasets that included GitHub and the UC Irvine Machine Learning Repository(38,39). Images from The PlantSeg dataset at https://doi.org/10.5281/zenodo.13293891 were used. The images included a range of disease manifestations such as discoloration, including environmental parameters such as temperature, humidity, and soil moisture, were gathered using IoT-enabled sensors deployed in agricultural fields. A total of 1,000 images and corresponding contextual measurements were gathered from multiple locations to ensure dataset diversity.

Data Preprocessing: Preprocessinginvolves applying separately to the two data types to ensure compatibility with the model. The visual data underwent resizing to 224x224 pixels, normalization to arrange of [0,1], and augmentation techniques such as rotation, flipping and cropping to enhance model generalizability. Contextual data were cleaned by addressing missing values using mean imputation and normalized so that all variables fall within the same scale.

Model Architecture: The hybrid CNN-ANN model consisted of two primary modules: CNN Module & ANN Module in below figure.

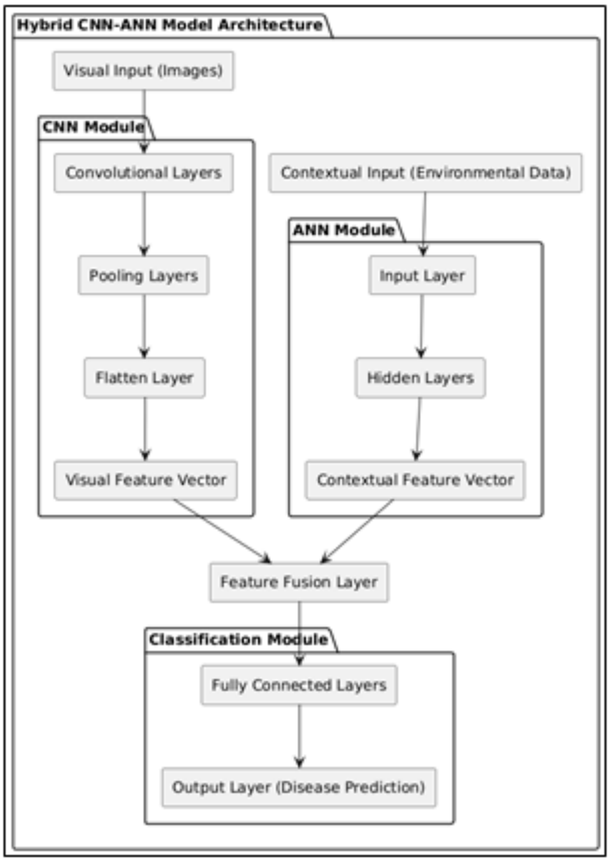


Figure 7: Schematic representation of the proposed hybrid CNN–ANN architecture, where image-based features obtained from convolutional and pooling layers are combined with contextual features from an ANN, followed by feature fusion and classification using fully connected layers to predict plant disease.

CNN module:

a) Itwas designed to extract visual features from the preprocessed plant leaf images.

b) A pre-trained ResNet50 architecture was used to extract features, with the final fullyconnected layer replaced to adapt to the specific plant disease dataset.

c) The CNN module generated a feature vector representing hierarchical visual patterns, such as textures, edges, and discolorations.

ANN Module:

a) The ANN module was responsible for processing the contextual data. It included input layer which accepted normalized environmental features, two hidden layers with 64 and 32 neurons respectively, and an output feature vector representing relationships between the contextual variables and plant disease risks.

b) **Feature Fusion**: The outputs from the CNN and ANN modules were concatenated to generate a unified feature vector which is passed to the final classification layers for disease prediction.

c) **Training and Testing:** The dataset was split into training (70%), validation (15%), and testing (15%) sets. The hybrid model was trained using the Adam optimizer with a learning rate of 0.001, and categorical cross-entropy was used as the loss function. Early stopping was implemented thus preventing overfitting and patience parameter of 10 epochs. The training phase involved 50 epochs having batch size of 32.

Evaluation Metrics: Model performance was evaluated using the following metrics. (1) Accuracy: to measure the percentage of correctly classified samples, (2) Precision, recall,and F1-Score: to assess the model's ability to identify each disease class effectively, (3)Confusion Matrix: to give insights into classification, and (4) AUC-ROC Curve: to assess model's performance in distinguishing between disease classes.

Implementation: The model has been made using Python using the Keras and TensorFlow libraries. The images and contextual data handling were done using OpenCV and NumPy respectively. The experiments were executed on a GPU-enabled system to enhance computational efficiency. The mentioned model of CNN+ANN integrates CNN's expertise for image analysis and ANNs for contextual data processing and handling. This makes a secure and reliable framework for plant disease detection with details of architecture as depicted below in Table 1.

Table 1: Overview of the hybrid CNN–ANN model setup, detailing the CNN architecture (ResNet50), ANN structure, feature extraction and fusion methods, dataset composition, and key training parameters such as optimizer, learning rate, and loss function.

Component	Details
CNN Architecture	Pre-trained ResNet50
CNN Adaptation	Additional fully connected layer added for the plant disease dataset
Feature Extraction Method	Convolutional layers, pooling operations, and ReLU activation
Visual Features Captured	Lesions, discoloration, and texture anomalies in plant images
ANN Inputs	Environmental and soil metrics (temperature, humidity, pH levels)
ANN Structure	Input layer → Hidden Layer 1 (64 neurons) → Hidden Layer 2 (32 neurons)
Feature Fusion Method	Direct concatenation or weighted fusion
Dataset	15 crops and their associated diseases
Training Samples per Disease	200 – 270
Testing Samples per Disease	150 – 190
Optimizer	Adam
Learning Rate	0.001
Loss Function	Categorical Cross-Entropy

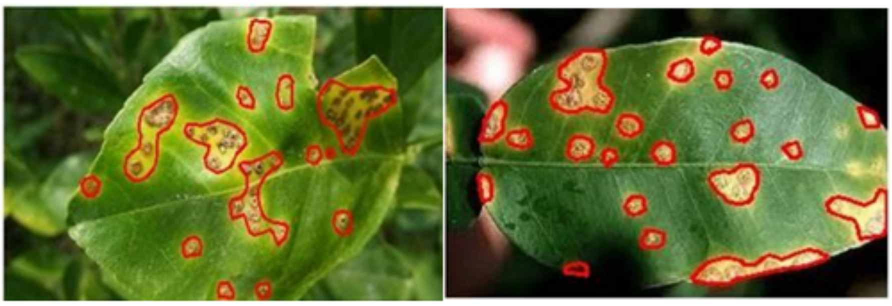
RESULTS

The images illustrated below are samples of the raw input images of plant leaves exhibiting disease symptoms.

(a) (b)

Figure 8 (a) and (b): Representative plant leaf images showing symptoms of disease such as leaf spots, discoloration, and texture abnormalities, which are utilized as visual inputs for disease classification in the proposed framework.

The below images are annotated samples of images of Figure 8(a) and (b) illustrating annotated images of diseased leaves, highlighting regions affected by infections using red boundary markings. These annotations were performed to delineate symptomatic areas, aiding in the identification and quantification of disease severity. Figure 9(a) shows localized patches of infection, whereas Figure 9(b) presents a more widespread distribution of lesions across the leaf surface. These annotations provide a critical visual reference for training ML models in automated plant disease detection systems.



(a) (b)

Figure 9(a) and (b): Representative plant leaf images showing disease symptoms with annotated lesion regions (highlighted in red), demonstrating the identification and localization of infected areas for use in model development and validation.

Below shows an input lemon plant leaf and the model identified and generated the image alongside with segmentation performed and output as “sunburn disease”.

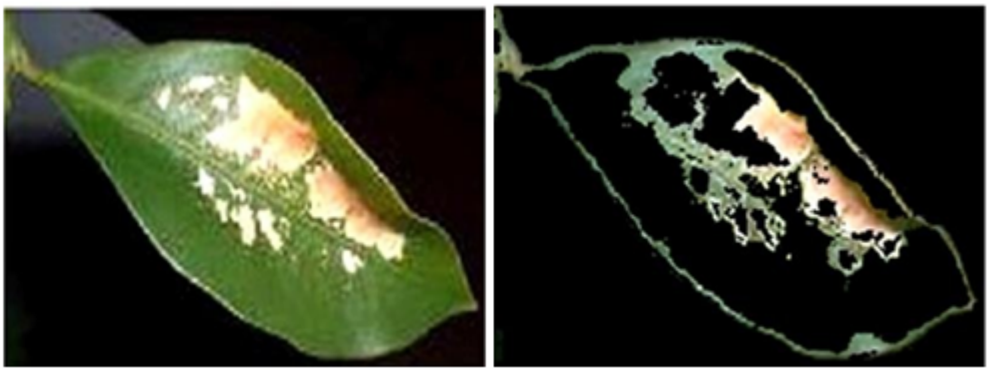


Figure 10(a) and (b): Comparison of original and segmented plant leaf images, where the segmented output highlights infected regions against the background, illustrating the preprocessing step used to enhance feature extraction for disease classification.

Figure 10(a) shows the raw image of a lemon plant leaf exhibiting visible symptoms of infection, characterized by dis-colored patches on the leaf surface. Figure 10(b) presents the segmented output image, where the affected regions are distinctly highlighted and separated from the healthy areas. The segmentation process enables precise identification of infected regions, facilitating quantitative analysis and disease severity assessment. The details of different crops along with Disease, Training samples, Testing samples, Accuracy, AUC, Sensitivity, Specificity is depicted below in Table 2.

Table 2: Comparative performance metrics of the proposed plant disease detection model for multiple crop species, presenting dataset distribution (training and testing samples) and evaluation metrics including detection accuracy, AUC, sensitivity, and specificity.

Crop	Disease	Training Samples	Testing Samples	Detection Accuracy (%)	AU C	Sensitivity (%)	Specificity (%)
Rice	Rice Blast	200	150	92.5	0.93	94.2	90.8
Wheat	Leaf Rust	250	170	90.1	0.91	89.7	91.2
Mango	Powdery Mildew	190	160	88.3	0.89	86.5	90.1
Tomato	Early Blight	260	190	93.8	0.94	95.1	92.3
Potato	Late Blight	220	170	89.9	0.90	91.3	88.2
Coconut	Bud Rot	210	150	87.5	0.88	89.0	85.6
Sugarcane	Red Rot	270	190	91.7	0.92	92.4	91.1
Banana	PanamaWilt	240	180	90.3	0.91	91.8	89.1
Papaya	Papaya RingSpot	200	150	88.9	0.89	89.5	87.7
Cotton	Boll Rot	230	160	89.4	0.90	88.8	90.2
Tea	Blister Blight	260	190	91.2	0.91	92.1	90.5
Coffee	Coffee Rust	200	150	93.0	0.93	94.3	91.5
Chickpea	FusariumWilt	250	170	89.6	0.90	88.9	90.3
Groundnut	Tikka Leaf Spot	270	190	90.7	0.91	91.4	90.1
Mustard	Alternaria Blight	220	150	87.8	0.88	88.3	87.2

DISCUSSION

The below diagram in Figure 11 illustrates the performance metrics such as AUC, Sensitivity, Specificity, Detection accuracy, Samples used for testing and training for several of the plant types covered in evaluation phase, and diseases that were detected. The results of our study demonstrate the effectiveness of the ML modelsin detecting plant diseases with high accuracy across different varieties of crops. Here, we discuss the findings in detail, focusing on detection accuracy, Area Under the Curve (AUC), sensitivity and specificity for each plant disease.

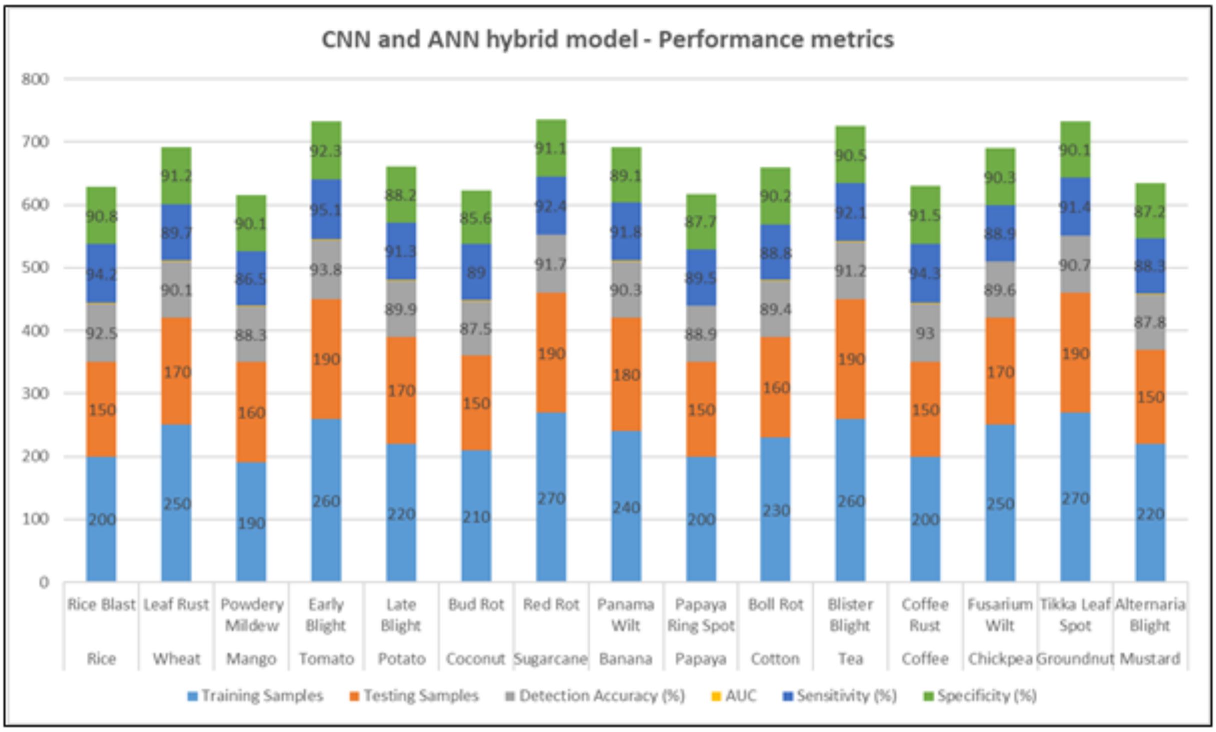


Figure 11: Graphical representation of the performance of the hybrid CNN–ANN model for different crop–disease combinations, illustrating dataset distribution (training and testing samples) and key evaluation metrics such as detection accuracy, area under the curve (AUC), sensitivity, and specificity.

High-Performance Cases: The models distinguish well for Rice Blast, Tomato Early Blight, and Coffee Rust, achieving detection accuracies of 92.5%, 93.8%, and 93.0%, respectively. These high accuracies were then proved by a robust AUC value of 0.93 or higher. This shows exceptional model discrimination between diseases and healthy plant samples. For these diseases, sensitivity values exceeding 94% demonstrate that the models were highly effective at correctly detecting infected samples, while specificity values above 90% indicate a low rate of misclassifying healthy samples. The highly accurate results are due to clear symptomatic features in the input data and enough training samples.

Moderate Performance Cases: Moderate performance was seen for diseases like Powdery Mildew in mango and Bud Rot in coconut. The detection accuracies were 88.3% and 87.5%, respectively. The AUC values ranged between 0.88 and 0.89, indicating acceptable but not exceptional classification capability. The relatively lower sensitivity and specificity compared to high-performance cases suggest that subtle or overlapping disease symptoms may have made detection more challenging during training. Increasing the size and diversity of the training dataset could help improve performance for these crops as depicted in table below:

Table 3: Indicates that the proposed model achieved a detection accuracy of 88.3% for powdery mildew in mango and 87.5% for bud rot in coconut, with corresponding AUC values of approximately 0.89 and 0.88, respectively.

Crop	Disease	Detection Accuracy (%)	AUC
Mango	Powdery Mildew	88.3	~0.89
Coconut	Bud Rot	87.5	~0.88

Comparative Analysis of Sensitivity and Specificity: The sensitivity and specificity values provide useful insights into the model's performance. Sugarcane Red Rot showed strong results with a sensitivity of 92.4% and a specificity of 91.1% which demonstrates a balanced detection of both diseased and healthy samples. Similarly, Tea Blister Blight achieved a sensitivity of 92.1% and a specificity of 90.5% which indicates reliable identification of infected leaves while maintaining accurate classification of healthy ones. Potato Late Blight showed slightly higher sensitivity (91.3%) than specificity (88.2%), implying the model was more prone to identifying diseased samples but could potentially over classify healthy samples as diseased. This slight trade-off might necessitate additional refinement in the model's feature extraction process.

Impact of Training Samples: The quantity of training samples data significantly influenced the model's performance. For crops like Sugarcane and Groundnut the training sample size was on the higher side (270) and detection accuracy exceeded 90% - with balanced sensitivity and specificity. In contrast, diseases such as Coconut Bud Rot and Mustard Alternaria Blight had relatively fewer training samples, which corresponded with slightly lower detection accuracies of 87.5% and

87.8%. This suggests that increasing the number of training samples could potentially improve the model's performance for these cases. The details of crops, disease, sensitivity, specificity, training samples and accuracy are illustrated below in Table 4.

Table 4: Performance summary for selected crop–disease combinations, including sensitivity, specificity, training sample size, and detection accuracy of the proposed disease detection model.

Crop	Disease	Sensitivity (%)	Specificity (%)	Training Samples	Accuracy (%)
Sugarcane	Red Rot	92.4	91.1	—	—
Tea	Blister Blight	92.1	90.5	—	—
Coconut	Bud Rot	—	—	210	87.5
Mustard	Alternaria Blight	—	—	220	87.8

Overall Performance Trends: The overall detection accuracy across all crops was consistent and well above 87% with almost every disease attaining 90% and higher. The model showcases robustness in dealing with diverse datasets and varied indicative patterns. The AUC values were in the range of 0.88 to 0.94, making the model reliable in differentiating diseases and healthy samples. Furthermore, the sensitivity values, which measure the model's capability to correctly detect diseased samples, were generally higher than the specificity values.

CONCLUSION

The findings of this study underscore the transformative potential of models in automating plant disease detection diagnostics with high accuracy and reliability. Across 15 crops and their associated diseases, detection accuracy consistently exceeded 87%, with most diseases surpassing 90%. High-performing cases, such as Rice Blast (92.5%), Tomato Early Blight (93.8%),and Coffee Rust(93.0%),exhibited strong precision supported by robust AUC values (≥ 0.93), sensitivity (>94%), and specificity (>90%).The hybrid CNN-ANN architecture was instrumental in achieving these results by integrating both visual and contextual data for holistic disease diagnosis. While the CNN module excelled in extracting hierarchical spatial and textural features from plant images, the ANN module processed environmental and soil metrics, capturing non-visual factors influencing plant health. This fusion of data streams through the feature fusion module enabled the model to effectively address diseases with overlapping symptoms but distinct environmental triggers such as Panama Wilt in Banana and Red Rot in Sugarcane.

The success of the hybrid model can also be attributed to several architectural and methodological innovations. The CNN module's use of convolution layers and data augmentation techniques improved generalization across diverse symptomatic patterns, while the ANN module enhanced sensitivity and specificity by identifying correlations in contextual data. Furthermore, pre-trained architectures (e.g., ResNet50), optimizers like Adam and early stopping during training mitigated overfitting and maximized the utility of limited training samples, particularly for diseases like Mustard Alternaria Blight and Coconut Bud Rot. The combination of these factors not only validated the robustness of the model across varying datasets but also demonstrated its scalability and adaptability to diverse agricultural scenarios. This study highlights the immense potential of hybrid AI solutions to revolutionize plant disease detection, paving path for further advancements through larger datasets, transfer learning, and multimodal approaches. These innovations promise to enhance global agricultural productivity and sustainability, offering accurate and dependable diagnostic support to farmers worldwide.

ABBREVIATIONS

CNN: Convolutional Neural Network, ANN: Artificial Neural Network, DL: Deep Learning, AUC: Area under Curve, AI: Artificial Intelligence, RELU: Rectified Linear Unit, ML: Machine Learning.

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Author Contributions

Rajesh Singh: Conceptualization, Methodology, Software Implementation, Validation, Visualization, Writing-Original Draft, Gaurav Agarwal: Supervision, Motivation and Guidance, Akash Sanghi: Supervision and Counselling.

Conflict of Interest

The corresponding author declares on behalf of all other authors that there is no conflict of interest.

Declaration of Artificial Intelligence (AI) Assistance

No Generative AI or AI-assisted technologies were used in the preparation of this manuscript.

Ethics Approval

It is not applicable.

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