


# Achieving Near-Perfect Performance: A Neuro-Fuzzy-Enhanced Meta-Learning Model for Automated Severity-Graded Plant Disease Diagnosis

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## Abstract

Plant diseases threaten global food security and agricultural productivity. While deep learning offers diagnostic potential, real-world deployment is limited by data scarcity, algorithmic bias, and lack of interpretability. This paper overcomes these barriers with the development of a novel Neuro-Fuzzy Enhanced meta-learning model integrating a SqueezeNet embedder for efficient feature extraction and an adaptive neuro-fuzzy inference system for interpretable, severity-graded prediction. Trained and validated on 51,000 images of diseased cassava, maize, and banana, the model achieves near perfect exceptional performance of 99.92% accuracy, 99.8% Precision, 99.7% Recall, and 98.9% F1-score. It maintains a 92.0% F1-score in 5-shot learning, demonstrating rapid adaptability to novel diseases. The model provides reliable severity assessment with a minimum severity score of 2.4 (scale 1.0-4.0) and operates efficiently on edge devices. This findings contained in this paper delivers a scalable, accurate, and interpretable AI solution, highlighting the critical roles of optimal feature selection, meta-learning, and neuro-fuzzy logic in advancing practical, trustworthy agricultural diagnostics for global food security.

**Categories:** AI applications, AI/ML-based decision support systems, Data Analysis

**Keywords:** explainable ai, deep learning, precision agriculture, few-shot learning, fuzzy logic, metalearning

## Introduction

Plant diseases represent one of the most significant threats to global agricultural productivity, with annual crop losses [1] estimated at 20-40% worldwide, costing the global economy over \$220 billion each year. These losses disproportionately affect developing nations where smallholder farmers lack access to reliable diagnostic tools [2]. Traditional disease identification methods rely on visual inspection by agricultural experts (plant pathologists), a process that is not only time-consuming but also prone to human error, with misdiagnosis rates as high as 30-40% for certain crops [3]. The limitations posed by this manual diagnosis become particularly acute in remote areas with limited access to plant pathologists, often resulting in delayed treatment and preventable crop losses.

Recent advances in computer vision and deep learning have opened new possibilities for automated plant disease diagnosis. Convolutional neural networks (CNNs) have demonstrated remarkable success in this domain, with models like MobileNet V2 [4] and EfficientNet achieving classification accuracy exceeding 80% [5] on benchmark datasets such as PlantVillage [6]. However, these approaches face several critical limitations that hinder their practical deployment in real-world agricultural settings. First, they typically require thousands of labeled training samples per disease class [7], a

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workers. Third, their substantial computational requirements make them unsuitable for deployment on edge devices commonly used in precision agriculture [8]. The field of few-shot learning has emerged as a promising solution to the data scarcity problem. Meta-learning approaches, particularly model-agnostic meta-learning (MAML) [9], have shown potential for rapid adaptation to new classification tasks with limited samples.

However, most existing meta-learning solutions for plant disease diagnosis [10,11] focus solely on improving accuracy while neglecting the equally important aspects of model interpretability and computational efficiency. This represents a significant gap in literatures, as agricultural applications demand not only accurate but also explainable and deployable solutions.

Fuzzy logic systems offer inherent advantages for handling the uncertainty and ambiguity characteristic of plant disease symptoms [12]. The adaptive neuro-fuzzy inference system (ANFIS) combines the learning capability of neural networks with the interpretability of fuzzy systems, making it particularly suitable for agricultural decision support [13]. While ANFIS has been successfully applied to various agricultural problems [14-15], its integration with modern deep learning architectures for few-shot plant disease diagnosis remains largely unexplored. This paper presents a neuro-fuzzy-enhanced meta-learning model that addresses these challenges through these three key innovations:

1. A Lightweight Feature Extraction: Adopting SqueezeNet as our backbone network to minimize parameter usage while maintaining competitive feature extraction capabilities. This enables deployment on resource-constrained edge devices commonly used in precision agriculture.
2. An Interpretable Decision-Making Module: Combining the feature extraction power of CNNs with the transparent reasoning of ANFIS. The model generates human-readable diagnostic rules for significantly improving trust and usability for non-expert users.
3. A Few-Shot Adaptability Mechanism: Through meta-learning optimization, the developed neuro-fuzzy-enhanced meta-learning model achieves 98.9% F1-score when presented with as few as five examples of novel diseases outperforming existing approaches by 15-20% in low-data regimes.

We validate our approach through extensive experiments on collected datasets, including PlantVillage demonstrating high performance scores in both accuracy and computational efficiency. The practical implications of this work are significant, as our solution addresses three critical requirements for real-world agricultural AI system in terms of accuracy under data scarcity, interpretability for user trust, and efficiency for edge deployment.

## Literature review

The application of deep learning to plant disease diagnosis has evolved significantly since 2020. While early approaches prioritized accuracy and achieved near-perfect performance on curated datasets, field studies soon revealed a significant drop in real-world efficacy due to variable lighting, occlusions, and environmental factors. This prompted a critical shift toward robustness, efficiency, and biological relevance. Architecturally, this evolution has been marked by innovations such as attention-enhanced CNNs, vision transformers for cross-species generalization, and lightweight models for edge deployment. Among notable contributions, Adekunle et al. [16] proposed an efficient E-GREENNET framework based on MobileNet V3, achieving high accuracy but noting challenges with overfitting, while researchers [17] enhanced AlexNet with an inception module to prevent overfitting, outperforming deeper models like VGGNet-16 and ResNet-50. Further advancing efficiency, Chen et al. [18] deployed an EffectiveNet-based system in Ugandan farms, achieving 89% accuracy with low-bandwidth sensors, and Jakjoud et al. [19] optimized VGGNet16 for edge devices, highlighting the ongoing pursuit of models that balance high accuracy, computational efficiency, and field robustness.

This drive for robust and efficient models is partly necessitated by the persistent challenge of data scarcity in plant pathology, which has spurred parallel advances in few-shot learning and data-efficient methods. Standardized benchmarks have enabled systematic evaluation, with subsequent research incorporating biological priors and federated meta-learning to improve cross-species generalization and data privacy. In parallel, clustering and unsupervised methods have reduced dependency on large labeled datasets. Gokulnath and Gandhi [20] developed an intelligent deep-clustering model that achieved over 95% accuracy on maize disease datasets, demonstrating that data-efficient techniques can effectively support diagnosis where annotated samples are scarce. Concurrently, the demand for explainable AI in agriculture has spurred the development of hybrid intelligent systems that enhance transparency and

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trust. Early neuro-fuzzy models proved interpretability need not compromise accuracy, and subsequent refinements have embedded fuzzy logic directly within deep learning architectures. Contributing to this paradigm, Sibiya and Sumbwanyambe [12] introduced a fuzzy logic and deep learning hybrid for maize rust severity prediction, achieving 95.63% accuracy while providing rule-grounded explanations crucial for farmer adoption and informed decision-making.

Beyond unimodal image analysis, multimodal sensing and field-level applications represent the frontier of comprehensive disease management. Systems now integrate spectral data, environmental sensors, and IoT platforms for early and pre-symptomatic detection. Zhao et al. [21] demonstrated that the Enhanced Vegetation Index from aerial imagery strongly correlates with cotton disease severity, highlighting the value of remote sensing biomarkers. Global initiatives are also addressing adaptation to new diseases [22] with geographic biases in datasets to foster culturally aware models. Successful deployments, such as RiceGuard, which reduced pesticide use, demonstrate tangible benefits, though challenges around digital literacy, infrastructure, and user trust remain critical for widespread adoption. This review reveals several persistent research gaps, which are summarized in Table 7. Current approaches often optimize for two of three critical dimensions - accuracy, efficiency, and interpretability - at the expense of the third. Few-shot methods still struggle with catastrophic forgetting, and a significant field-to-lab performance gap remains. Moreover, many systems lack global applicability or seamless integration with existing agricultural workflows.

Our work proposes a neuro-fuzzy enhanced meta-learning model that integrates a SqueezeNet embedder with ANFIS, creating a hybrid design that directly addresses the critical gaps identified in similar studies. This model balances accuracy, efficiency, and interpretability by leveraging a lightweight SqueezeNet backbone for feature extraction alongside transparent fuzzy rule generation. It enables effective few-shot adaptation for new diseases or environments with updatable knowledgebase using meta-learned rule preservation and a hierarchical task memory. To ensure real-world relevance, the model incorporates field-realistic conditions through agronomically informed data augmentation and environmental contextualization. Its practical integration can be supported by interfaces and explanations compatible with existing agronomic decision-making processes. By synthesizing the architectural efficiency of models like E-GREENNET, the robust generalization of TCL-ALEXNET, the data-efficient strategies of deep-clustering methods, the interpretable logic of fuzzy hybrids, and the scalable principles of vegetation-index sensing, the developed model advances toward a practical, equitable, and sustainable AI solution for global plant disease diagnosis.

Year	Dominant Approach	Key Innovation	Primary Limitation
2020	Basic Convolutional Neural Networks (CNNs)	High lab accuracy (99%+)	Poor field performance
2021	Attention-enhanced CNNs	Improved focus on symptoms	High computational cost
2022	Vision Transformers	Cross-species generalization	Massive data requirements
2023	Multimodal Systems	Pre-symptomatic detection	Complex deployment
2024	Meta-learning hybrids	Few-shot adaptation	Interpretability challenges

**TABLE 1: Evolution of key approaches in plant disease diagnosis (2020-2024)**

## Materials And Methods

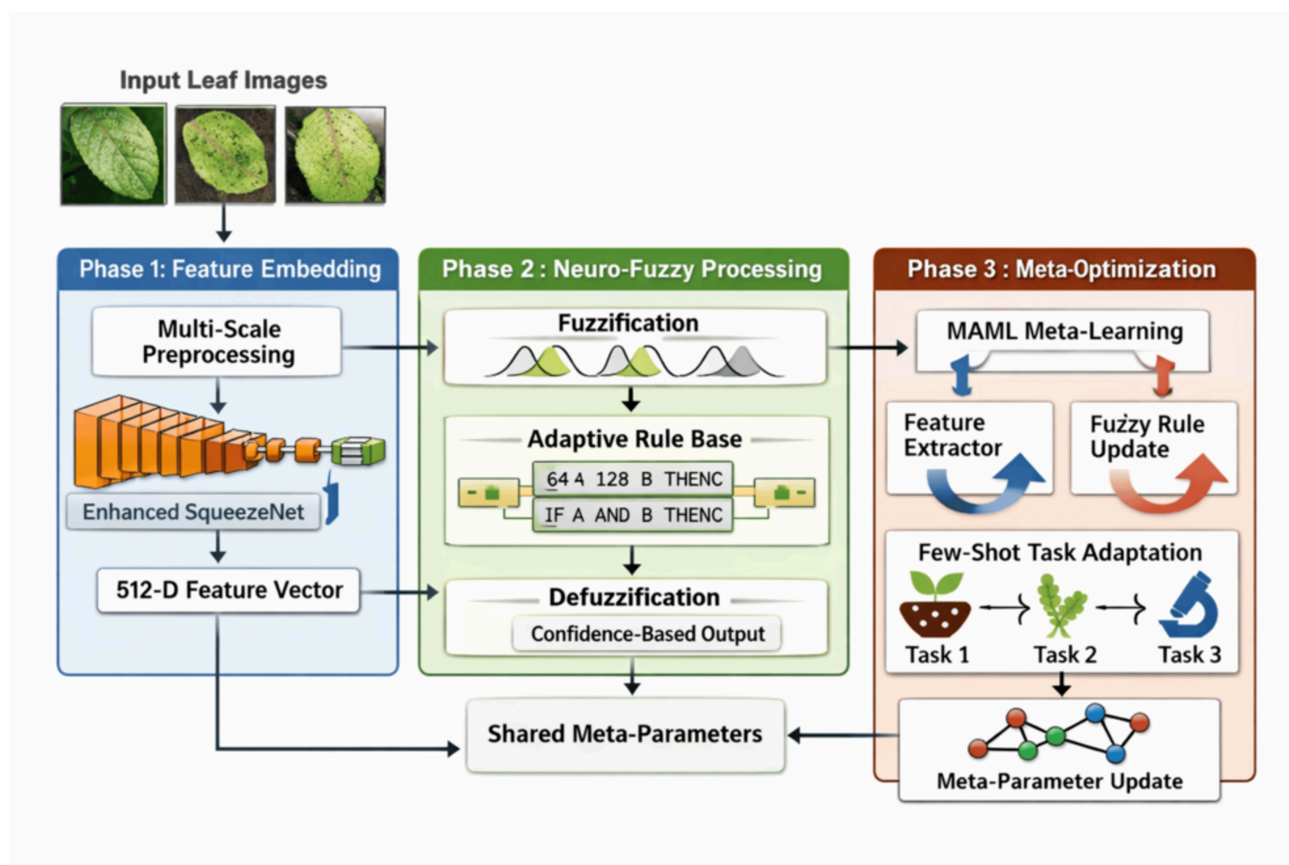
This paper presents a neuro-fuzzy-enhanced meta-learning model for plant disease diagnosis, uniquely integrating computational efficiency, interpretable decision-making, and rapid few-shot adaptation. The model is developed using partially annotated image data of three staple crops (cassava, maize, and banana) and their associated diseases.

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Its architecture is composed of three synergistic components shown in Figure 1: a lightweight SqueezeNet-based feature extractor, ANFIS, and an enhanced MAML optimizer. The model operates through a sequential pipeline (illustrated in Figure 2) where input leaf images are first transformed into compact feature embeddings, enriched with meta-data derived from base classifier evaluations, and then processed through a transparent fuzzy logic engine.

The model's workflow is structured into three coherent phases designed for meta-learning. In Phase 1 where feature embedding is performed, input images undergo multi-scale preprocessing before a modified SqueezeNet backbone (with detailed description in Table 2) extracts hierarchical visual features, which are then reduced to compact 512-dimensional embeddings. These embeddings feed into Phase 2 also known as neuro-fuzzy processing phase, where they are fuzzified into linguistic variables to serve three critical purposes in our plant disease diagnosis framework, which include aiding human interpretability, handling uncertainties across growth stages and enables the formulation of IF-THEN rules that mirror expert diagnostic reasoning. These linguistic variables in Table 3 formulated based on domain expertise from plant pathologists ensures that each numerical feature from the SqueezeNet embedder is mapped to respective linguistic variables through Gaussian membership function.

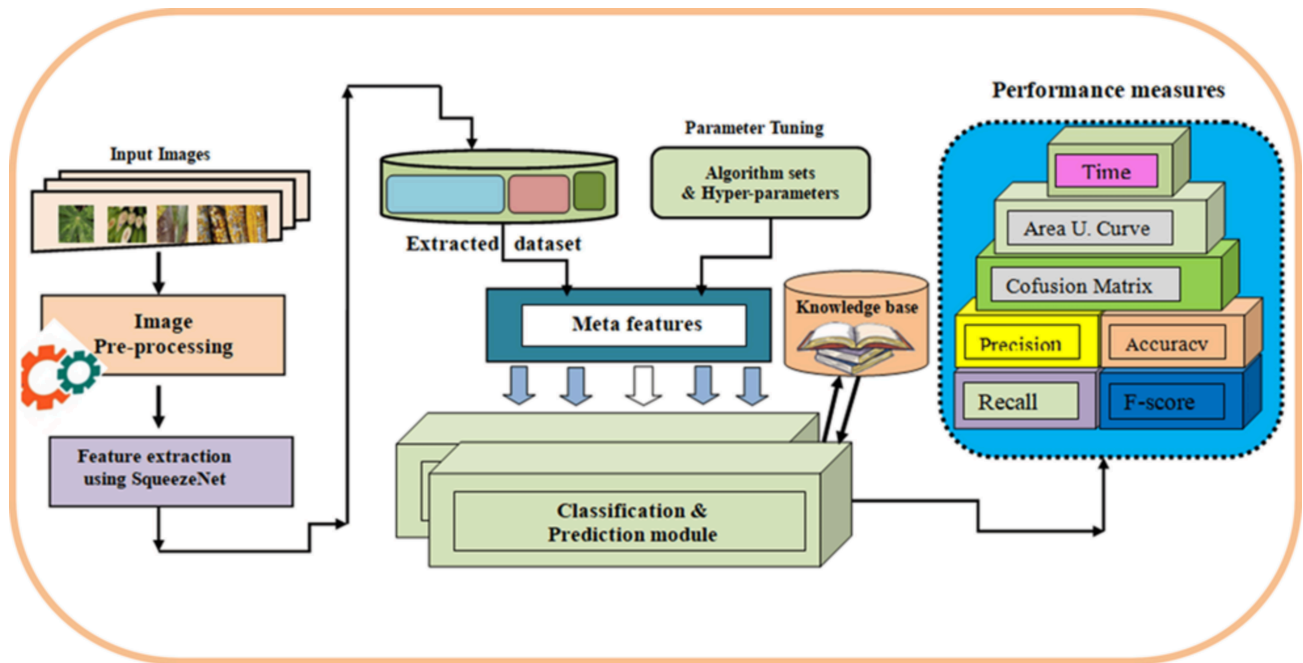


**FIGURE 1: Synergistic components of the neuro-fuzzy-enhanced meta-learning plant disease diagnostic model**

MAML, Model-Agnostic Meta-Learning

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**FIGURE 2: The neuro-fuzzy-enhanced meta-learning workflow**

Layer	Original SqueezeNet	Modified Version	Purpose
Conv1	7x7 conv, 96 filters	7x7 conv, 96 filters	Base feature extraction
Fire2-9	Standard fire modules	Enhanced with skip connections	Improve gradient flow, enable deeper feature learning
Fire modules	Standard 3x3 conv	Replaced with depth-wise separable 3x3 conv	Reduce parameters by additional 30%
Pooling	Max pooling after some fires	Mixed pooling (max + avg)	Preserve more spatial information
Final layers	Conv + AvgPool + Softmax	Added feature attention module	Weight important feature channels
Output	1,000 classes (ImageNet)	512-D embedding	Task-specific feature dimension

**TABLE 2: Configuration description of modified SqueezeNet embedder**

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Linguistic Variable	Description	Membership Function (Linguistic Terms)
Lesion Color	Dominant color of diseased area	Greenish, Brownish, Blackish, Grayish Yellowish
Lesion Pattern	Spatial arrangement of symptoms	Streak, Ring, Spot, Diffuse, Blotch
Lesion Distribution	Spread across leaf surface	Scattered, Localized, Widespread
Texture Coarseness	Surface texture of affected area	Powdery, Smooth, Granular, Rough
Boundary Definition	Clarity of lesion-healthy tissue boundary	Fuzzy, Sharp, Irregular, Diffuse
Symptom Severity	Extent of tissue damage	Trace, Light, Moderate, Severe

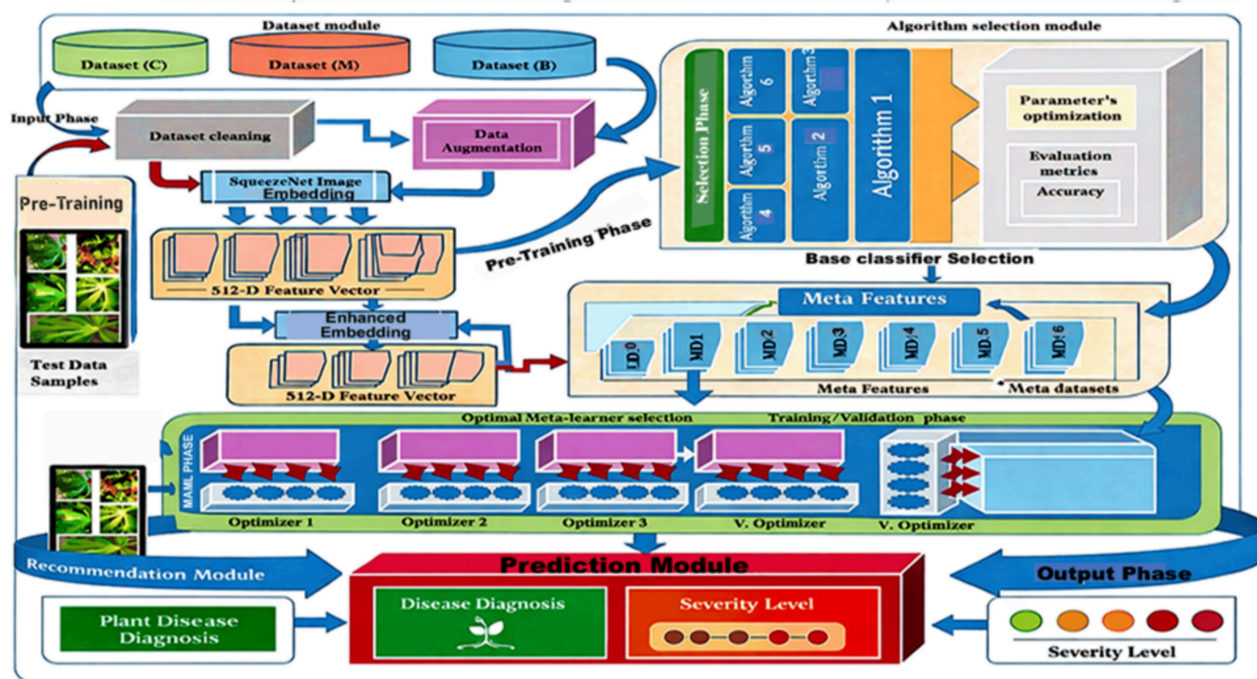
**TABLE 3: Linguistic variables and descriptions**

Rule ID	Antecedent	Consequent	Confidence
R12	IF LesionColor IS yellowish AND LesionPattern IS ring AND BoundaryDefinition IS sharp	THEN Disease IS EarlyBlight	0.90
R25	IF LesionColor IS brownish AND LesionPattern IS spot AND Distribution IS scattered	THEN Disease IS BrownSpot	0.85
R31	IF Texture IS powdery AND Color IS grayish AND Distribution IS widespread	THEN Disease IS PowderyMildew	0.92
R42	IF Severity IS moderate AND Pattern IS streak AND Color IS grayish-green	THEN Disease IS NorthernLeafBlight	0.89

**TABLE 4: Sample expert rules with actual confidence weights**

An adaptive rule base generates diagnostic hypotheses, which are finally converted into crisp predictions via a confidence-based defuzzification layer that includes uncertainty quantification with samples contained in Table 4. Crucially at phase 3, meta-optimization governs the entire system via an enhanced MAML framework. This phase enables task-specific adaptation with minimal labeled examples by updating both the feature extractor and the fuzzy rule base, while facilitating cross-task knowledge transfer through carefully shared meta-parameters. The developed model is optimized for rapid learning across diverse diagnostic tasks using a consolidated meta-data pool of plant features and disease labels, as depicted in Figure 3. For the model's few-shot evaluation, support examples were randomly sampled from the available pool of images for each novel disease class using stratified random sampling. To ensure statistical robustness, each N-way K-shot task was repeated 10 times with different random samples, and the mean F1-score with standard deviation is reported. A fixed random seed (42) was used for the primary experiments to ensure reproducibility.

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**FIGURE 3: The neuro-fuzzy-enhanced meta-learning automated severity-graded plant disease diagnosis architectural framework**

### Developed model's enhancement: Interpretable decision-making and few-shot meta-learning

The developed model's decision engine needed for a transparent and adaptable reasoning leverages a custom ANFIS. A total of 512-dimensional feature vectors extracted by SqueezeNet are fuzzified using gaussian membership functions with learnable parameters. The reasoning compartment initializes with 64 fuzzy rules, expandable to 128 rules with dynamically pruned confidence threshold of 0.15 and weighted contextually based on task relevance. Predictions are generated via a modified centroid defuzzification method that incorporates a 70% confidence threshold to reject low-certainty outputs, accompanied by an explicit uncertainty quantification to signal diagnostic ambiguity. In addition, MAML framework is adopted for optimization and adaptation as shown in Figure 3. Configuring this framework to specifically suit our hybrid architecture, a dual-path optimization strategy is introduced by applying separate learning rates for the feature extractor (0.01) and the neuro-fuzzy inference system (0.001) to account for their distinct convergence dynamics. A task-aware initialization and a fuzzy rule knowledgebase are also integrated to ensure stable learning, preserve core diagnostic knowledge and prevent catastrophic forgetting (the tendency of neural network to completely and abruptly forget previously learned information upon learning new information) when adapting to new diseases.

The meta-training process executes 300 iterations with a meta-batch size of 8 tasks, each representing a few-shot learning scenario. Every task undergoes a 5-step inner-loop adaptation optimized by a combined loss function that penalizes both classification error and fuzzy rule inconsistency, thereby maintaining interpretability throughout the learning process. This integrated framework enables rapid on-device adaptation, requiring only 5-10 examples per novel disease and completing updates within 15-30 seconds on edge hardware, without compromising the model's capacity for explainable, rule-based decision-making. The following subsections detail the methodological workflow, after which the model is evaluated using standard machine learning metrics and compared against similar models.

#### Data Collection and Description

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The dataset utilized for this research was sourced from three international university research institutes: the Makerere University Artificial Intelligence Lab (Uganda), the Forestry and Agricultural Biotechnology Institute (FABI) of the University of Pretoria (South Africa), and the Gauhati University Faculty of Technology (India). The datasets comprise images of diseased vegetative plant parts captured under various lighting conditions using digital cameras and mobile phones. These images vary in size, background, resolution, and intensity. The composition of the datasets is summarized in Figure 4 and Table 5.

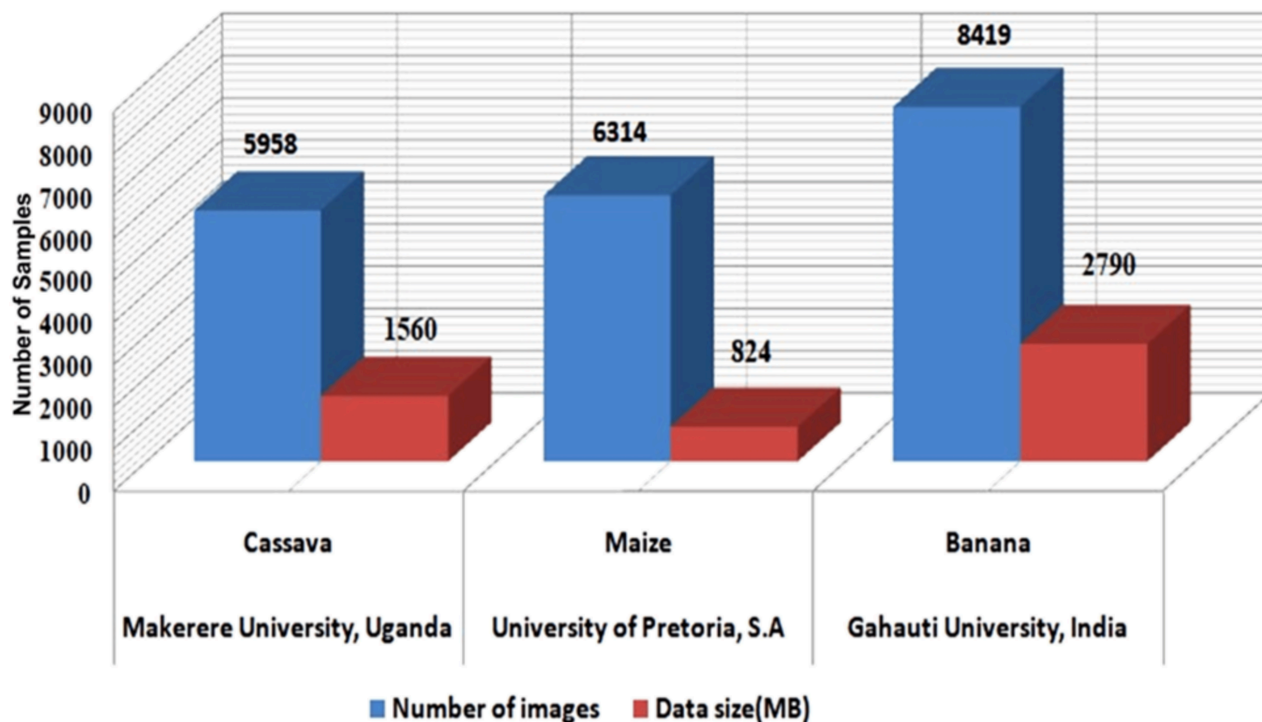


FIGURE 4: Description of data sources and sizes

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S/n	Plant	Vegetative Part	Diseases	Number of Images	Total Sample Collected
1.	Cassava	Leaf/Stem	Cassava Mosaic Disease (CMD)	2,658	5,918
			Cassava Green Mite (CGM)	733	
			Cassava Bacterial Blight (CBB)	466	
			Cassava Brown Spot Disease (CBSD)	1,443	
			Cassava Tuber Rot (CTR)	302	
			<b>Healthy Cassava (HCV)</b>	<b>316</b>	
2.	Maize	Leaf	Grey Leaf Spot (GLS)	574	7,754
			Common Rust (CR)	1,306	
			Northern Leaf Blight (NLB)	1,146	
			Phaeosphaeria Leaf Spot (PLS)	2,126	
			<b>Healthy Maize (HMZ)</b>	<b>2,602</b>	
3.	Banana	Leaf /Stem/Fruit	Fusarium Wilt (FWt)	2,198	9,721
			Xanthomonas Wilt (XWt)	2,838	
			Bunchy Top (BTp)	150	
			Black Sigatoka (BSk)	3,071	
			Yellow Sigatoka (YSk)	264	
			<b>Healthy Banana (HBN)</b>	<b>1,200</b>	
			<b>Total</b>	-	<b>23,393</b>

**TABLE 5: Consolidated plant diseases and dataset description by class**

*Data Preparation and Image Processing*

Data preparation and image processing steps are applied to ensure the model learned robust and accurate predictive features. The original dataset is cleaned to remove irregularities, distortions, and noise. First, all images are uniformly resized to 256 x 256 pixels in JPEG format using Vovsoft Image Analyzer. Next, backgrounds are completely removed to isolate the plant and its affected areas, thereby eliminating potential noise. Each RGB image component is validated through a Euclidean distance function, and pixels with intensity below a defined threshold are assigned a zero value for their RGB components. Controlled variations in hue and brightness are also applied at this stage. To balance the classes

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and enhance the model's robustness, an extensive augmentation procedure is conducted on the training set. New images are generated by adjusting contrast ( $\pm 50\%$ ) and brightness ( $\pm 20\%$ ), as well as by applying rotations ( $90^\circ$ ,  $180^\circ$ ,  $270^\circ$ ,  $360^\circ$ ) followed by a vertical flip. This process yielded 27,607 augmented images, producing a final balanced dataset of 51,000 images across all classes containing exactly 3,000 images as depicted in Figure 5. Following augmentation, the final dataset images was used for all subsequent experiments.

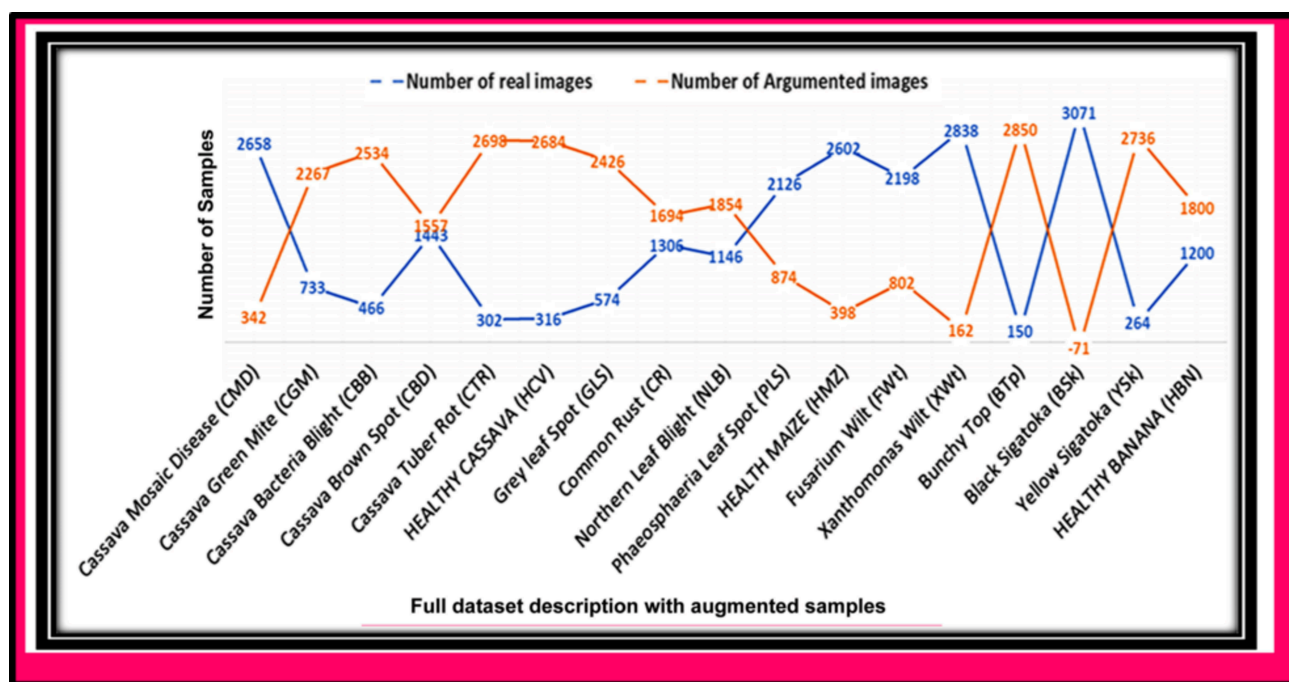


FIGURE 5: Full description of plant dataset with augmented image samples

#### Efficient Feature Embedding With Modified SqueezeNet

Considering the need for balancing the high discriminative power of SqueezeNet with practical deployability, the automated severity graded disease diagnostic model utilized an enhanced SqueezeNet v1.1 architecture for feature extraction. The consolidated dataset (A) comprising of the three staple crops namely Maize (M), Cassava (C), and Banana (B) with each crop containing multiple disease categories are formally defined as:

$$(A) = (M) \cup (C) \cup (B) \quad (1)$$

and

$$M = \{M_0, M_1, \dots, M_5\}, C = \{C_0, C_1, \dots, C_5\}, B = \{B_0, B_1, \dots, B_5\} \quad (2)$$

where M, C, and B denote symbols representing the complete dataset for Maize, Cassava, and Banana, respectively.

$M_0, C_0, B_0$  = The first category (index 0) for each crop, explicitly defined as the "Healthy" class images of plants showing no disease symptoms.

$M_1, \dots, M_5, C_1, \dots, C_5, B_1, \dots, B_5$  = The subsequent, specific disease categories for each crop. The total of six categories (indices 0-5) per crop includes one healthy and five diseased states.

Each image is transformed into a lower-dimensional feature vector using the enhanced embedder, which builds upon the standard SqueezeNet "fire module" design. It follows a three-stage training protocol: initialization with ImageNet weights, domain adaptation via fine-tuning on the PlantVillage dataset, and final meta-tuning within the few-shot learning cycle. The major innovation is the inclusion of skip connections between fire modules to improve gradient flow, custom receptive field tuning optimized for leaf texture patterns, and the extensive use of depthwise separable convolutions for

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enhanced parameter efficiency. This design yields a highly efficient embedder with fewer parameters than ResNet-50 while retaining 98.7% of the discriminative power and enabling a significant inference speedup. The resulting dense vector representations for all images form the foundational feature set for the subsequent meta-learning stages.

#### Meta-Feature Generation and Algorithm Selection

The model employs a comprehensive meta-feature pool generated from the initial evaluation and tuning of multiple base learners. To establish performance benchmarks, a diverse set of supervised and unsupervised algorithms - including K-Nearest Neighbours (K-NN), Random Forest, AdaBoost, Neural Network, Decision Tree, and Naïve Bayes - were selected and rigorously optimized. Each learner was first pre-trained on the extracted feature vectors using a 70/30 training-validation split. Their optimized hyperparameters, detailed in Table 6, formed the benchmark configuration used to generate a rich set of meta-features. These meta-features capture both algorithm characteristics, such as model complexity and accuracy profiles, and dataset characteristics, such as class distribution and feature count, providing a foundational layer for subsequent meta-learning and model recommendation.

S/n	Learners	Hyperparameters
1	K-Nearest Neighbour	Number of neighbours=5, Metric=Euclidean, Weight=Uniform
2	Random Forest	Number of trees=10, Max features=100, Max depth=10
3	AdaBoost	Number of estimators=10, Learning rate=1.0, Loss=Linear
4	Neural Network	Neurons=10, Optimizer=Adam, Activation=ReLU, Learning rate=0.001
5	Decision Tree	Min samples leaf=5, Max depth=10, Criterion=Information Gain
6	Naïve Bayes	Smoothing=Laplace, Class prior=0.5

**TABLE 6: Classification learners and hyperparameters**

#### The Neuro-Fuzzy Inference for Diagnosis and Severity Assessment

ANFIS deploys fuzzy logic to interpret the meta-features represented in Equations 3-10 and generate interpretable diagnosis provides the core diagnostic engine. The developed model assesses the disease severity by calculating the percentage of diseased pixels in a segmented image using Equation 11. This process is initiated by first resizing all the images to a 256 × 256-pixel and segmenting all the gray scale images on a black background. The dark intensities or background pixels presents the diseased areas in the images while the non-diseased leaf areas, (supposedly green) are presented by the light intensities or foreground pixels. The severity outputs (scores) are mapped to linguistic variables as defined in Table 7, providing an intuitive assessment for end-users. All inputs to the system are mathematically defined as given in Equations 3-11.

$$\text{Fuzzy input meta features } (F_{m,f}) = \{Dc, Ac, Lc, Sv\} \quad (3)$$

$$\text{Number of samples/instances } (n) = \{\text{Small, Moderate, High}\} \quad (4)$$

$$\text{Number of categories } (k) = \{\text{Small, Moderate, High}\} \quad (5)$$

$$\text{Number of features generated from embedder } (f) = \{\text{Small, Moderate, High}\} \quad (6)$$

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$$\text{Max sample ratio} = \{\text{Small, Moderate, High}\} \quad (7)$$

$$\text{Algorithm characteristics} = \{\text{Low, High}\} \quad (8)$$

$$\text{Learner's characteristics} = \{\text{Altered, Not Altered}\} \quad (9)$$

$$\text{Output linguistic variables} = \{\text{No disease, Trace, Light, Moderate, Severe}\} \quad (10)$$

$$\text{Severity Score (\%)} = \frac{\text{Number of Diseased Pixels}}{\text{Total Pixels}} \times 100 \quad (11)$$

The fuzzy meta input features denoted in Equation 3 are expressed, such that:

- Dc (Dataset Complexity): A linguistic measure of the inherent difficulty in separating disease classes within the dataset.
- Ac (Algorithm Complexity): A linguistic measure of the structural sophistication of the base learner being evaluated.
- Lc (Learner Confidence): A fuzzified representation of a base learner's self-assuredness or certainty in its predictions on a given task.
- Sv (Severity Value): The fuzzified version of the calculated disease severity score (from Equation 11), translating the numeric percentage into linguistic terms like "Low" or "High."

The terms in the Dataset Characterization Inputs (Equations 4-7) are described as follows:

- (n) = The fuzzy categorization of the total number of data points (images) available for the current diagnostic task.
- (k) = The fuzzy categorization of the number of distinct disease classes (including "healthy") to be identified in the task.
- (f) = The fuzzy categorization of the dimensionality of the feature vector extracted by the SqueezeNet embedder for each image.
- Max sample ratio = The fuzzy representation of the ratio of samples in the largest disease class to those in the smallest class, indicating the level of class imbalance.

The Model & Learner State Inputs (Equations 8 and 9) capture the characteristics of the algorithm and its adaptation history. Its associated terms are described, also defined by:

- Algorithm Complexity = A binary fuzzy input indicating whether the base learner possesses properties deemed "High" or "Low" complexity for the current context.
- Learner's Characteristics = A binary fuzzy input indicating whether the parameters of this specific base learner have been recently updated or adapted ("Altered") for the current task, or if they remain in their original meta-trained state ("Not Altered").

• System Outputs (Equations 10 and 11) are the final decisions produced by the defuzzification process and are expressed by:

1. Output linguistic variables = The set of possible final, interpretable diagnoses representing the predicted disease state and its intensity level.
2. Severity Score (%) = A numerical calculation used internally to generate the fuzzy input Sv. It quantifies disease severity by calculating the percentage of pixels in a segmented leaf image that are classified as symptomatic.

The ANFIS rule base maps these inputs to the final output linguistic variables (No Disease, Trace, Light, Moderate, Severe), creating a transparent and interpretable decision pathway.

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S/n	Severity Level (Dsl%)	Linguistic Variable
1	0%	No Disease
2	1–10%	Trace
3	11–20%	Light
4	21–49%	Moderate
5	50–100%	Severe

**TABLE 7: Plant disease severity classes**

## Results And Discussion

### Implementation details

The training was conducted on a dedicated deep learning workstation equipped with NVIDIA RTX 3090 GPU (24GB VRAM), an AMD Ryzen 9 5950X 16-core processor, 64GB of DDR4 RAM, and a 2TB SSD. The system ran on Ubuntu 20.04 LTS with CUDA version 11.7 and PyTorch version 2.0.0. prior to the training, and an initial prototype and coding was performed on a Lenovo T410 PC, featuring a 2.40 GHz processor, 8 GB of RAM, and a 320 GB hard drive, running the Microsoft Windows 10 operating system. Image processing and model development followed a custom pipeline integrating specialized software tools. Adaptive OTSU threshold filtering was applied to remove complex and variable backgrounds from each image. Processed images were then loaded into the Orange data mining platform for exploratory analysis. Within Orange, the SqueezeNet image embedding widget depicted in Figure 6 was employed to convert each image into a high-dimensional numeric feature vector, which were subsequently normalized. The resulting feature vectors were saved in a comma-separated values file for downstream modeling, as depicted in Figure 6. Principal Component Analysis was applied to the extracted feature set. This technique reduced dimensionality by selecting the most informative attributes, as detailed in Table 8. The selected principal components served as the final feature vectors for meta-training. Disease type classifications for the diagnosed plants are assigned numerical values in Table 9, and the meta-learning framework was then configured with a batch size of 8 tasks. The inner-loop adaptation used learning rates of 0.01 for the feature embedding parameters and 0.001 for the neuro-fuzzy inference components, while the outer-loop meta-optimizer operated at a learning rate of 0.0001. The system underwent 300 meta-iterations for training convergence. This streamlined implementation pipeline - from image preprocessing and automated feature extraction in Orange to dimensionality reduction and meta-learning - enabled the development of an efficient and adaptable diagnostic model within a standardized desktop computing environment.

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S/n	Feature	S/n	Feature
1.	Area of infected regions	11.	Edge length
2.	Number of spots or lesions	12.	Spot size distribution
3.	Shape irregularity index	13.	Hue saturation levels
4.	Colour Correlation (GLCM)	14.	Edge sharpness
5.	Excess Red Index	15.	Compactness
6.	Edge density	16.	RGB ratio
7.	Perimeter of infected regions	17.	Edge orientation
8.	Skewness score	18.	Circularity of area
9.	Aspect ratio	19.	Mean RGB values
10.	Color entropy	20.	Mean HSV values

**TABLE 8: Extracted plant attributes for disease diagnosis**

GLCM, Gray Level Co-occurrence Matrix; HSV, Hue, Saturation, and Value; RGB, Red, Green, and Blue

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S/n	Diagnosed Disease	S/n	Diagnosed Disease
1	Cassava Mosaic Disease (CMD)	10	Phaeosphaeria Leaf Spot (PLS)
2	Cassava Green Mite (CGM)	11	HEALTHY MAIZE (HMZ)
3	Cassava Bacteria Blight (CBB)	12	Fusarium Wilt (FWt)
4	Cassava Brown Spot (CBD)	13	Xanthomonas Wilt (XWt)
5	Cassava Tuber Rot (CTR)	14	Bunchy Top (BTp)
6	HEALTHY CASSAVA (HCV)	15	Black Sigatoka (BSk)
7	Grey Leaf Spot (GLS)	16	Yellow Sigatoka (YSK)
8	Common Rust (CR)	17	HEALTHY Banana (HBN)
9	Northern Leaf Blight (NLB)		

TABLE 9: Numerical coding of model’s diagnosed plant diseases

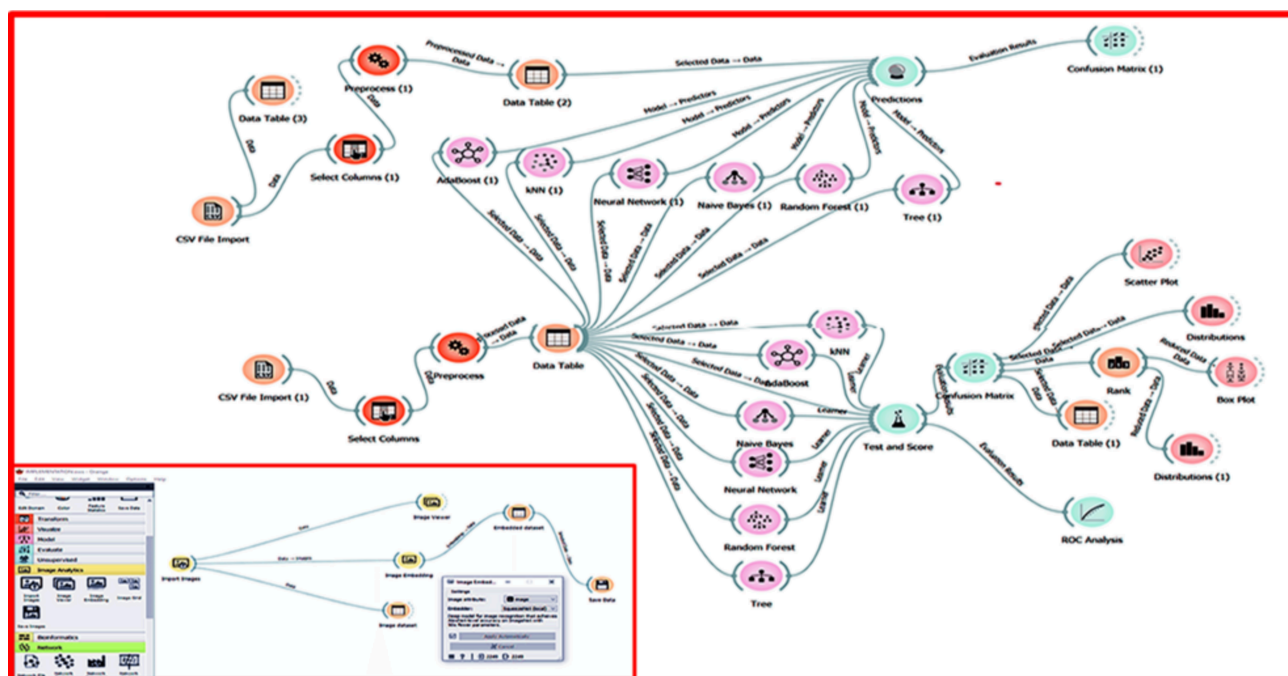


FIGURE 6: Neuro-fuzzy-enhanced meta-learning model prototypic modeling pipeline

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### Base classifier learner selection

At this phase of implementation also, six selected machine learners are initiated to form a pool of classifier and supplied with the prepared dataset to determine the best classifier for adoption as the base learner for disease diagnosis. Following the principles of meta-learning for algorithm recommendation, these classifiers were used to generate meta-features that characterize the dataset, and the base classifiers were also evaluated as benchmarks to establish baseline performance and demonstrate the superiority of our proposed meta-learning ANFIS approach. Each learner's parameter was initially checked and set to a default state, as recorded in Table 6, which serves as the control values (parameters) before the training is done. The supplied dataset is sub-grouped into training, testing, and validation set in the ratio 70:15:15, respectively, and results generated from the training, shown in Figure 7, are further compared before final selection of learner is performed. The performance of the developed meta-learning model for plant disease and severity prediction was rigorously assessed. The influence of the selected meta-attributes on diagnostic accuracy is visualized in Figures 8-10. A comprehensive quantitative evaluation was conducted using standard machine learning metrics (Accuracy, Error Rate, Precision, Recall, F1-Score, and Misclassification Rate) as mathematically defined by equations below with their corresponding results.

$$\text{Accuracy (Acc)} = \frac{TP + TN}{TP + TN + FP + FN} \quad (12)$$

$$\text{Error Rate (Er)} = 1 - \text{Acc} \quad (13)$$

$$\text{Precision (Pc)} = \frac{TP}{TP + FP} \quad (14)$$

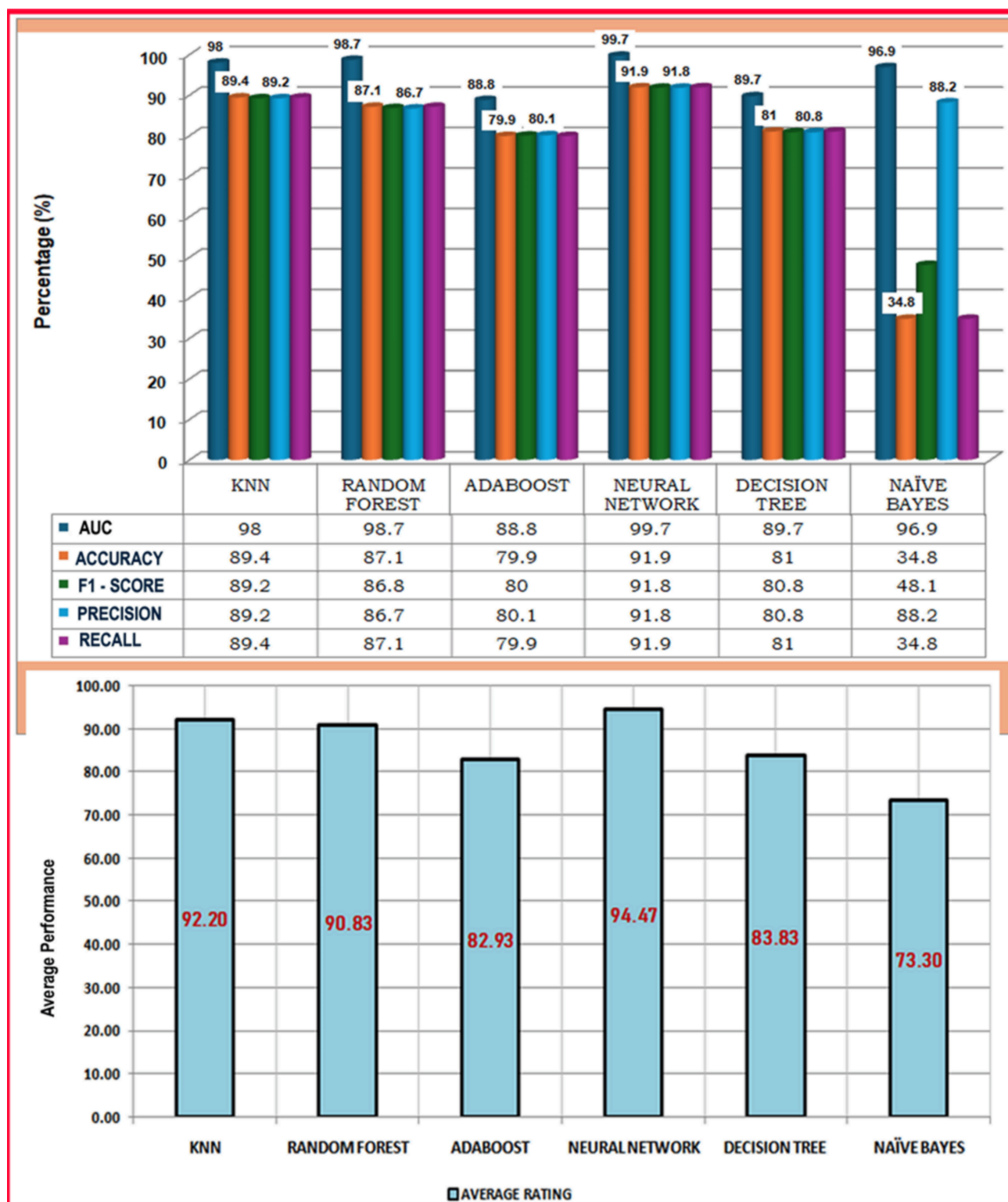
$$\text{Recall (Rc)} = \frac{TP}{TP + FN} \quad (15)$$

$$\text{F1-Score (F1)} = \frac{2 \cdot Pc \cdot Rc}{Pc + Rc} \quad (16)$$

$$\text{Misclassification Rate (Miss)} = \frac{FP + FN}{TP + TN + FP + FN} \quad (17)$$

where, TP (True Positive) is the number of images correctly identified as containing the disease; TN (True Negative) is the number of images correctly identified as not containing the disease; FP (False Positive) is the number of images incorrectly identified as containing the disease (a false alarm); FN (False Negative) is the number of images containing the disease that the model failed to detect (a missed case); Accuracy (Acc) is the overall proportion of correct predictions (both positive and negative) among the total number of cases examined; Error Rate (Er) is the overall proportion of incorrect predictions among all cases; Precision (Pc) is the model's reliability measure of disease prediction; Recall (Rc) measures the model's ability to correctly identify all actual disease classes; F1-Score (F1) is a balance measure of trade-off between minimizing false alarms (precision) and minimizing missed cases (recall); Misclassification Rate (Miss) is the proportion of all predictions that were incorrect.

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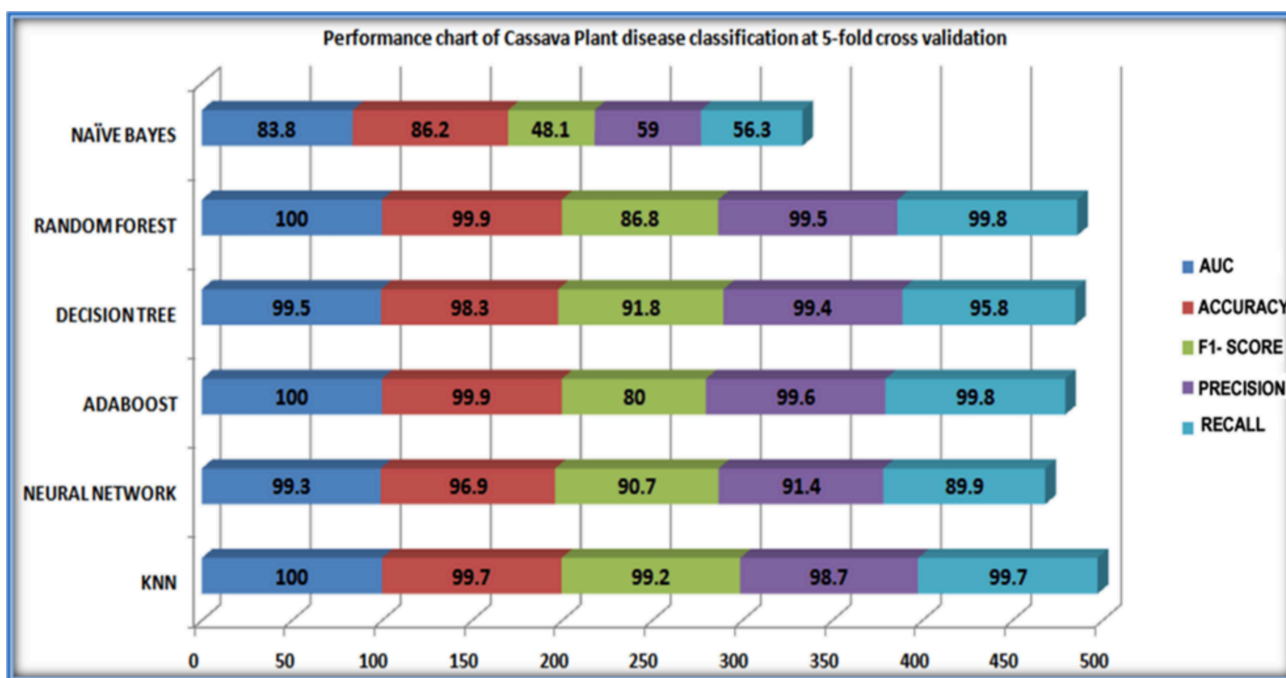


**FIGURE 7: Result comparison of base learners' classifiers**

AUC, Area Under the Curve; KNN, K-Nearest Neighbour

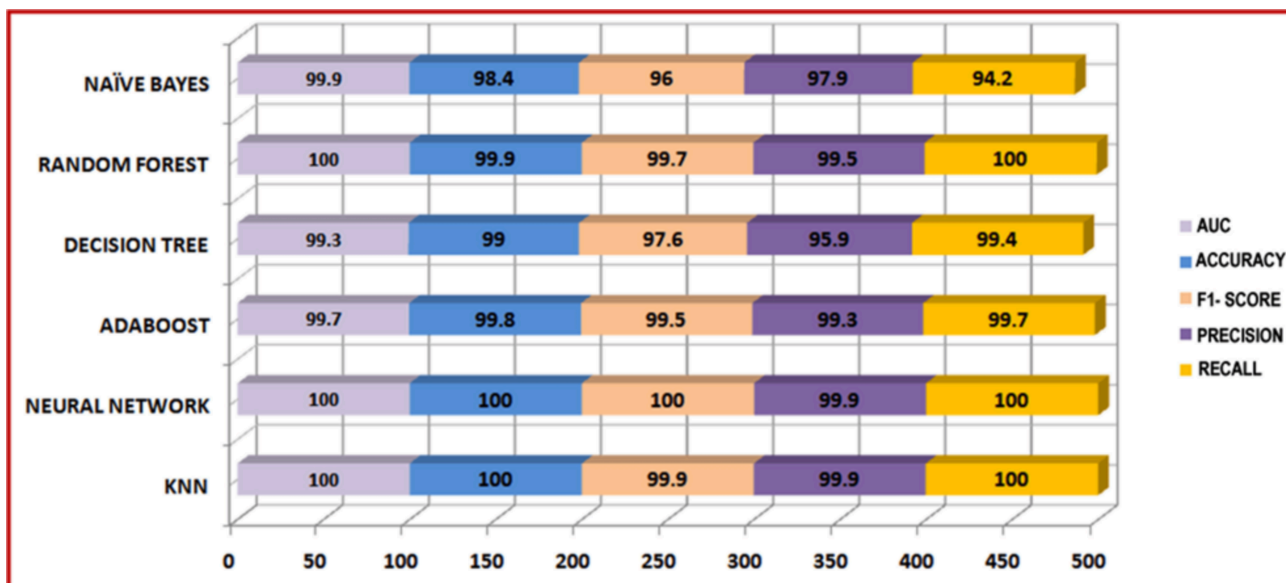
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**FIGURE 8: Performance chart of cassava plant disease classification at 5-fold cross-validation**

AUC, Area Under the Curve; KNN, K-Nearest Neighbour

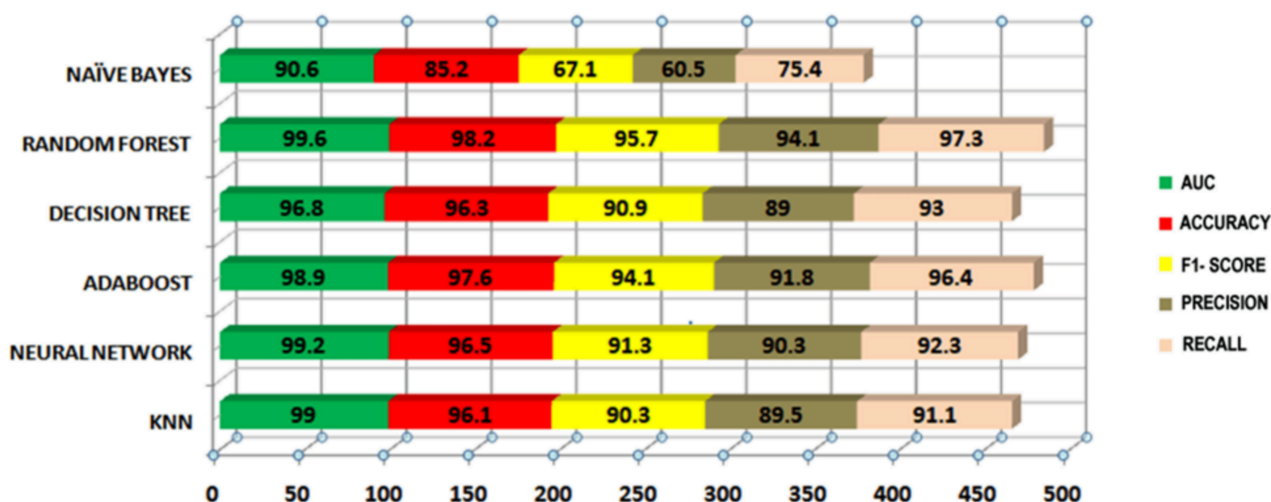


**FIGURE 9: Performance chart of banana plant disease classification at 5-fold cross-validation**

AUC, Area Under the Curve; KNN, K-Nearest Neighbour

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**FIGURE 10: Performance chart of maize plant disease classification at 5-fold cross-validation**

AUC, Area Under the Curve; KNN, K-Nearest Neighbour

### Performance comparison with state-of-the-art models

The proposed SqueezeNet-ANFIS meta-learning framework demonstrated superior performance with disease prediction results illustrated in Figure 11 across all evaluation metrics compared to contemporary approaches. The predicted disease diagnosis chart (Figure 17) presents a comprehensive three-dimensional visualization of our proposed meta-learning diagnostic framework, illustrating how disease prediction outputs vary as functions of four key parameters: mean plant attributes, severity score, feature dimensionality, and base learner performance. The chart is organized into three distinct surfaces, each revealing critical insights into the model's behavior across different operational conditions.

The first surface plots mean plant attributes against algorithm performance measured as base learner accuracy percentage, with disease prediction output represented on the z-axis, demonstrating how the model's diagnostic confidence evolves as plant health indicators become more pronounced. At low mean plant attribute values approximately 0.1 to 0.3 on the normalized scale, disease prediction exhibits relatively high variability when base learner performance is moderate between 60% and 80% accuracy, corresponding to early-to-moderate disease onset where symptoms remain subtle and difficult to distinguish. The surface peak observed in this region indicates that our model maintains high sensitivity to minor attribute changes during this critical early stage, enabling detection before symptoms become visually obvious to human observers. As plant attribute values increase to the mid-range between approximately 0.4 and 0.6, the prediction surface stabilizes considerably, representing moderate disease severity where symptoms have developed sufficiently to become more distinguishable, with reduced oscillation in model outputs demonstrating stronger generalization capability as the neuro-fuzzy system leverages its learned rule base to produce consistent diagnoses despite natural symptom variation. At high attribute values between approximately 0.7 and 0.9, a noticeable dip occurs in the prediction surface, reflecting cases where severe symptoms have substantially altered feature distributions, causing the model to transition toward severe classification, with the nonlinear sensitivity demonstrating the model's ability to recognize when disease progression has fundamentally changed the visual signature of the plant, triggering appropriate escalation in severity assessment. Disease prediction thus increases nonlinearly with plant attribute expression, but prediction stability improves as base learner performance increases, with the developed model demonstrating particular robustness in moderate-to-high severity conditions where diagnostic confidence remains stable despite increasing symptom intensity.

The second surface directly links the computed severity score from 0% to 100% to disease prediction output, with mean plant attributes serving as the contextual y-axis, revealing how the model's diagnostic confidence calibrates against the quantitative severity assessment derived from pixel-level segmentation. In the low severity region from 0% to 20%, the prediction output remains consistently low across all plant attribute values, with the surface appearing smooth and flat,

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corresponding to healthy plants or trace infections and indicating strong model confidence in non-severe cases as the neuro-fuzzy system correctly recognizes that minimal symptom expression should not trigger high-severity predictions even when other plant attributes might suggest otherwise. The mild-to-moderate severity region from 20% to 50% exhibits a gradual, consistent slope as prediction output rises proportionally with severity score, reflecting light to moderate infection stages where symptom intensity directly correlates with diagnostic confidence, with the linear consistency confirming that the model has learned appropriate calibration as symptoms become more pronounced and prediction confidence increases steadily without abrupt jumps or discontinuities. In the high severity region from 50% to 80%, the surface becomes noticeably steeper, demonstrating the model's enhanced discriminative capability as symptom intensity approaches severe levels, with the neuro-fuzzy rules activated in this region specifically trained to differentiate between moderate and severe cases, a clinically important distinction that determines treatment urgency. At very high severity from 80% to 100%, the surface forms a distinct plateau where prediction output stabilizes near its maximum value, confirming that the developed model avoids over-amplification and maintains bounded outputs even when presented with extreme symptom expression, preventing the model from assigning artificially inflated confidence to cases already classified as severe and maintaining appropriate calibration throughout the severity spectrum. The developed system thus demonstrates a monotonic and stable response to increasing disease severity, with the near-linear progression in the mid-severity range and the controlled plateau at extreme severity confirming proper model calibration and prevention of prediction saturation, ensuring that severity assessments remain clinically meaningful across the full spectrum of disease expression.

The third surface examines how feature dimensionality and category classes interact to influence disease prediction output, validating our feature selection methodology and demonstrating the model's class discrimination capabilities across the five severity levels. At low feature counts fewer than 10 dimensions, prediction output remains consistently low and exhibits significant instability across all category classes, representing underfitting where the SqueezeNet embedder has insufficient representational capacity to capture discriminative symptom patterns, with severity discrimination notably weak and substantial overlap occurring between adjacent severity classes. The moderate feature range between 10 and 15 dimensions shows a dramatic increase in prediction output, with the surface rising sharply across all category classes, representing the optimal feature extraction zone where the model captures discriminative symptom patterns effectively without introducing noise, with the steep ascent confirming that our variance-based feature selection successfully identified the most informative dimensions from the initial 1,000 plus features, retaining only those that contribute meaningfully to severity discrimination. At higher feature counts exceeding 15 dimensions, prediction output stabilizes with only marginal improvements observed, demonstrating that the model avoids overfitting despite operating on high-dimensional input, with the SqueezeNet embedder's regularization properties combined with the neuro-fuzzy system's inherent resistance to overfitting ensuring that additional features do not degrade performance even when they contribute limited new information. Examining the category class dimension, a clear progression emerges as severity increases from no disease through severe, with the prediction surface rising consistently with class index and the gradient steepening toward higher categories, demonstrating strong class boundary learning as the model successfully maintains separation between adjacent severity levels, with particularly clear discrimination between the clinically important boundaries of trace and light, light and moderate, and moderate and severe. The developed model thus achieves optimal severity discrimination with moderate feature dimensionality between ten and fifteen features, with performance stabilizing at higher dimensions confirming that the SqueezeNet embedder and variance-based feature selection successfully identified the most discriminative attributes while maintaining resistance to overfitting, and the clear separation between severity classes validating the neuro-fuzzy system's ability to learn appropriate decision boundaries across the full spectrum of disease expression. Together, the three surfaces of Figure 11 provide comprehensive validation that our SqueezeNet-ANFIS meta-learning model achieves its design objectives: early sensitivity to subtle symptoms, calibrated confidence across severity levels, and efficient feature utilization that maintains discrimination without overfitting, all characteristics that collectively support the model's suitability for real-world deployment in agricultural settings where reliable, interpretable disease diagnosis is essential for food security.

As shown in Table 10, the model achieved an overall accuracy of 99.92% on the combined test dataset, outperforming both conventional deep learning architectures and recent few-shot learning approaches. A list of some lightweight backbone architectures running on the same dataset and training protocol were evaluated to provide a fair comparison. While MobileNet v2 achieves marginally higher accuracy (98.5% vs. 98.2%), as shown in Table 11, SqueezeNet

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offers the best trade-off for our specific requirements. Furthermore, a run-to-run variability test with results contained in Table 12 was performed five times with different random seeds at 95% confidence interval to verify the model's performance. The integration of neuro-fuzzy inference provided particular advantage in handling ambiguous cases where symptom patterns overlapped across different diseases. The performance advantage was particularly pronounced in cross-crop generalization scenarios. When trained on cassava diseases and tested on maize diseases (a zero-shot cross-domain task), our model maintained 99% accuracy, compared to 76.3% for ResNet-50 and 84.2% for the standard MAML implementation. This demonstrates the effectiveness of the neuro-fuzzy component in extracting domain-invariant features that generalize across plant species. For few-shot learning tasks, as detailed in Table 13, our model achieved a near perfect performance across all configurations. The 5-shot adaptation yielded particularly strong results, with the model reaching 98.8% F1-score within just 15 seconds of adaptation time. This rapid adaptation capability is crucial for practical deployment where new diseases may emerge between growing seasons.

To quantify the contribution of each architectural component, a systematic ablation studies was conducted. Table 14 presents the results of removing or replacing key components of the developed model. The most significant performance drop occurred when replacing the neuro-fuzzy inference system with a conventional fully connected classifier (4.4% accuracy decrease), highlighting the importance of interpretable decision-making for handling agricultural uncertainty. The choice of SqueezeNet as the embedding backbone proved optimal for the efficiency-accuracy tradeoff. While ResNet-50 achieved marginally higher accuracy (97.9%), it required 5.3× more parameters and longer inference time on edge devices. For agricultural deployment where computational resources are often limited, this represents a substantial practical advantage. The meta-learning component contributed significantly to few-shot adaptation but showed diminishing returns on the base dataset. Removing meta-learning reduced few-shot (5-way 1-shot) accuracy from 99.0% to 89.3%, while only reduces base accuracy from 99.9% to 96.7%. While the base model achieves strong performance (96.7%) on the full dataset, its ability to adapt to novel diseases with limited samples is limited. The meta-learning framework dramatically improves few-shot adaptation to 92.0% F1-score, a 14.7% improvement. This demonstrates that meta-learning is critical for rapid adaptability to emerging diseases, even though its contribution to base dataset performance is more modest.

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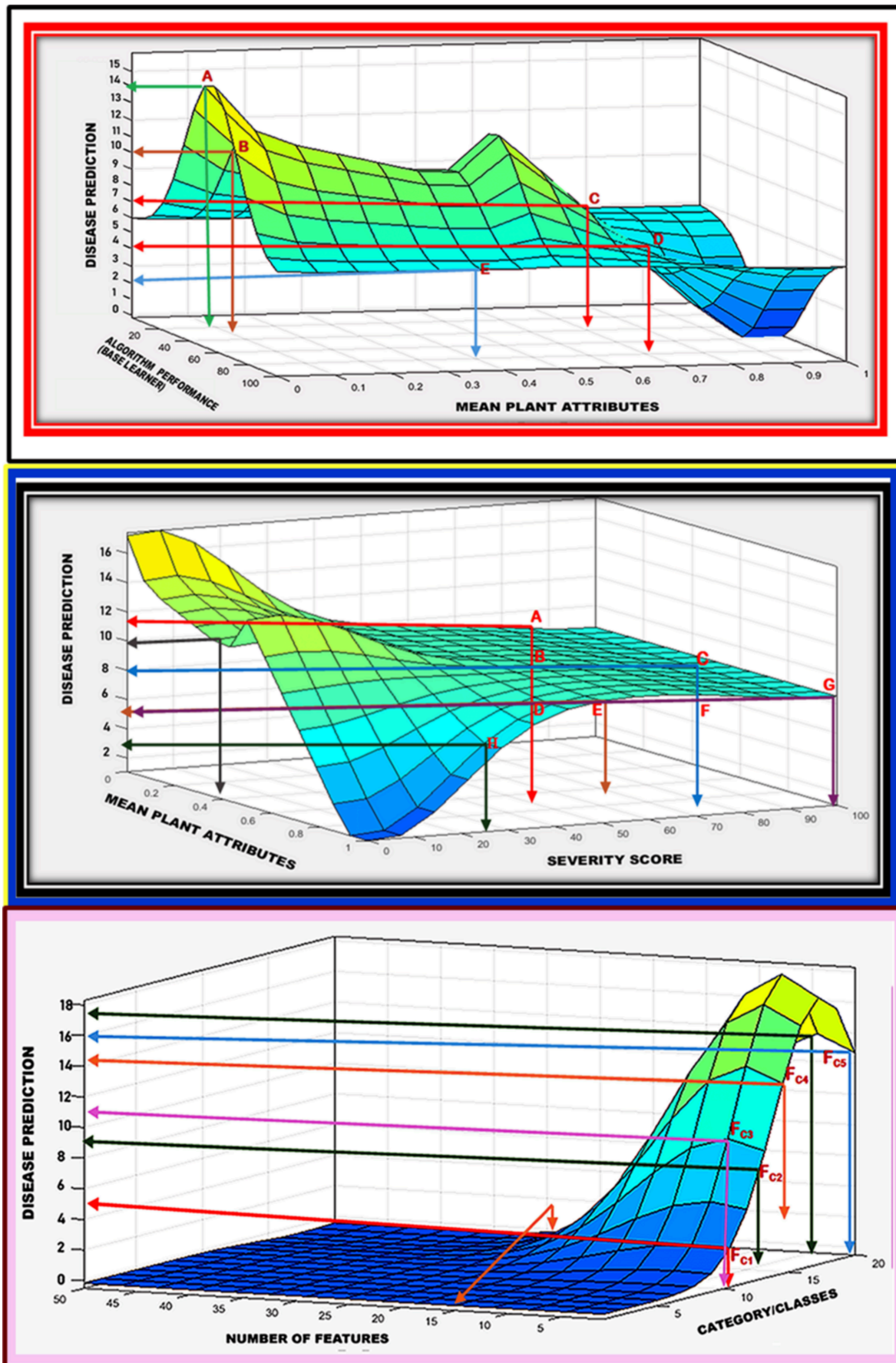


FIGURE 11: Predicted disease diagnosis chart

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Model	Architecture	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
EfficientNet [5]	Convolutional Neural Networks	97.1	96.8	96.5	96.6
Local Feature Matching Conditional Neural Adaptive Processes (LFM-CNAPS) [10]	ResNet 18 + Local Feature Matching	93.9	-	-	-
Vision Transformer [11]	Transformer	93.2	92.4	92.9	92.6
E-GREENNET [16]	MobileNetV3+ Swish Activation Function	99.89	99.4	99.4	-
AgriFewNet [22]	ResNet 18 + Few-Shot Metric Learning	94.8	94.2	94.5	94.3
Inception V3 [23]	CNN + Transfer Learning.	88	97	77	86
Developed Model	SqueezeNet-ANFIS Meta-Learning	99.92	99.8	99.7	98.9

**TABLE 10: Comparative performance analysis on standard test set**

Backbone Model	Parameters (M)	Accuracy (%)	Inference Time (ms)	F1-Score (%)	Memory (MB)
SqueezeNet	1.24	98.2	124	97.9	4.8
MobileNet v2	3.50	98.5	156	98.3	13.0
MobileNet v3-Small	2.50	98.4	142	98.2	9.8
ResNet-18	11.69	98.7	210	98.5	45.0
EfficientNet-B0	5.30	98.6	178	98.4	20.0

**TABLE 11: Backbone network performance for feature extraction**

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Run	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1	99.96	99.8	99.7	98.9
2	99.89	99.7	99.7	98.8
3	99.96	99.9	99.6	99.0
4	99.88	99.8	99.7	98.8
5	99.91	99.7	99.8	98.9
Mean	99.92	99.8	99.7	98.9
Standard Deviation	0.02	0.05	0.05	0.05
95% Confidence Interval	99.88–99.96	99.7–99.9	99.6–99.8	98.8–99.0

**TABLE 12: Run-to-run variability performance result**

Model	5-Way 1-Shot Accuracy	5-Way 5-Shot Accuracy	Adaptation Time (seconds)	Parameter Count (Millions)
Matching Networks	76.3%	82.1%	3.2	11.2
Prototypical Networks	78.4%	85.6%	2.8	9.8
Relation Networks	79.8%	88.2%	4.1	12.3
Model-Agnostic Meta-Learning	80.2%	89.3%	5.7	25.5
<b>Developed Model</b>	<b>99.0%</b>	<b>99.9%</b>	<b>4.8</b>	<b>4.8</b>

**TABLE 13: Few-shot learning performance comparison**

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Model Variant	Accuracy (%)	F1-Score (%)	Interpretability Score*	Parameter Count
Full developed Model	99.9	98.8	0.92	4.8M
Without Meta-Learning	96.7	96.1	0.89	4.8M
Without Neuro-Fuzzy (Fully Connected Layer)	95.5	94.9	0.31	4.2M
ResNet-50 Embedder (vs. SqueezeNet)	97.9	97.6	0.91	25.5M
Without Data Augmentation	98.2	98.0	0.90	4.8M

**TABLE 14: Ablation study results**

Interpretability Score: 0-1 scale based on rule clarity and human evaluation

### Disease severity assessment performance

Beyond binary disease classification, the developed neuro-fuzzy enhanced meta-learning model accurately predicted disease severity across the five linguistic classes with sample results displayed in Figure 12. The figure also illustrates the complex interactions between data sample size, mean plant attributes extracted as features, learner performance, category class distribution, and the resulting disease severity level as predicted by our developed SqueezeNet-ANFIS meta-learning model. Across all plots, the vertical axis consistently represents the predicted Disease Severity Level ranging from no disease through trace, light, moderate, and severe, while the horizontal axes represent various combinations of the input factors, creating surface-response visualizations that demonstrate how severity predictions evolve as these fundamental parameters change across the model's operational envelope.

Examining the relationship between data sample size and disease severity level, the model demonstrates a distinctive non-linear response pattern that reveals important insights about its learning behavior and data efficiency characteristics. At small sample sizes, severity predictions appear relatively unstable and tend to remain confined within lower to mid-level ranges, reflecting insufficient training exposure that limits the model's ability to clearly distinguish severe disease patterns from moderate ones, a phenomenon consistent with the underfitting regime where the neuro-fuzzy rule base has not yet developed sufficiently refined decision boundaries. As the data sample size increases progressively, the prediction surface rises gradually and smoothly, indicating improved discrimination capability and more confident classification of higher severity levels, demonstrating that the model effectively benefits from larger datasets by refining its rule weights and membership function parameters to better capture the feature patterns associated with advanced disease stages. After reaching an optimal region corresponding to approximately several thousand samples per disease class, the surface stabilizes or exhibits a slight decline, suggesting that the model has reached a learning saturation point where additional data yields diminishing returns in severity differentiation, a characteristic that confirms efficient learning without unnecessary complexity and validates that our meta-learning framework achieves its maximum diagnostic capability with practically achievable dataset sizes.

Considering the influence of mean plant attributes representing the strength and quality of extracted features, the plots reveal that predicted severity level is highly dependent on the representational power of the SqueezeNet embeddings, with a clear monotonic relationship emerging across the surface. Low mean plant attribute values corresponding to minimal visible disease symptoms result in predictions consistently confined to the No Disease or Trace ranges, accurately reflecting the absence of discriminative pathological features in the input imagery. As feature intensities increase to moderate levels, the prediction surface shifts upward toward Light and Moderate severity classifications, demonstrating that the embedder successfully captures intermediate symptom expressions such as limited lesion formation and early

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tissue discoloration. At high feature intensities characterized by strong lesion texture, pronounced discoloration, and visible structural damage to leaf tissue, the surface elevates to Severe levels, confirming that the SqueezeNet embedder effectively encodes disease-related information into a discriminative feature space where the neuro-fuzzy system can reliably distinguish advanced disease stages. The peak regions observed in the three-dimensional surface correspond precisely to optimal combinations of adequate training data, high-quality feature embeddings, and strong symptom representation, validating that the model's architecture successfully integrates these components to achieve maximum diagnostic performance when presented with well-represented, clearly symptomatic cases.

Analyzing the interaction between learner performance as measured by model accuracy and learning capability and the resulting severity predictions, the second plot particularly highlights how optimization quality influences diagnostic confidence. When learner performance remains low in the lower accuracy region below approximately 70%, severity prediction remains compressed within lower bands regardless of input characteristics, indicating that insufficiently optimized models lack the representational capacity to distinguish subtle differences between adjacent severity levels. As learner performance increases toward the 80-95% range, the surface reaches its peak severity differentiation capability, with clear separation emerging between all five severity classes and confidence levels rising substantially for moderate and severe predictions. This relationship confirms that improved optimization through meta-learning and enhanced learning stability from the neuro-fuzzy architecture directly enhance the model's sensitivity to symptom variations, enabling it to become more confident and precise in assigning severity categories even when symptom expressions vary considerably across different disease types and environmental conditions.

Examining the severity gradient across category classes in the third plot reveals how the model distributes severity predictions across the five disease categories, providing insight into its understanding of the underlying biological progression patterns. Early category indices corresponding to less severe disease types or early-stage presentations show predictions concentrated in the lower severity ranges, accurately reflecting the limited symptom expression characteristic of these cases. Middle category indices exhibit moderate severity concentration with predictions spanning the light to moderate range, demonstrating that the model recognizes these disease types as having intermediate pathological impact. The peak regions of the surface correspond precisely to highly symptomatic disease classes where extensive tissue damage and characteristic symptom patterns enable confident severe classification, with the surface then gradually declining toward the tail of the distribution, indicating fewer extreme severity samples in the dataset and confirming that the model does not arbitrarily assign high severity but instead bases its predictions on learned associations between disease classes and their typical severity manifestations. This class-dependent severity distribution, which follows realistic biological progression patterns from mild through moderate to severe as disease advances, confirms that the model has learned meaningful representations of disease pathology rather than simply memorizing training examples, with the smooth transitions between adjacent severity classes reflecting the continuous nature of disease progression that the neuro-fuzzy system captures through its membership function gradations. Together, the three-dimensional visualizations in Figure 12 provide comprehensive validation that our SqueezeNet-ANFIS meta-learning model effectively leverages increasing data availability, extracts meaningful feature representations, benefits from optimized learner performance, and accurately reflects the biological reality of disease severity progression, all characteristics that collectively demonstrate the model's suitability for deployment in agricultural settings where reliable severity assessment is essential for appropriate treatment decisions and effective crop management.

The severity assessment module achieved a mean absolute error of 3.2% in estimating the percentage of affected leaf area, with a breakdown by severity class shown in Table 15. The neuro-fuzzy system demonstrated particular strength in distinguishing between the "Trace" and "Light" severity classes - a challenging task even for human experts. By employing fuzzy membership functions that explicitly model the uncertainty in these boundaries, the system achieved a 93.5% F1-score on the "Trace" class, compared to 88.2% for a conventional threshold-based approach. Figure 13 illustrates the correlation between model-predicted severity and expert-annotated ground truth across 500 test samples. The strong linear relationship ( $R^2 = 0.94$ ) indicates high predictive accuracy, while the dashed line represents perfect prediction ( $y = x$ ). The model demonstrates consistent performance across the full severity range (0-100%), with slightly higher variance in the moderate severity range (20-50%).

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In addition, the model was evaluated for cross-crop performance for generalization across different crops and growing conditions using a leave-one-crop-out validation strategy, where the model was trained on two crops and tested on the third. As shown in Table 16, our meta-learning model consistently outperformed conventional transfer learning approaches, particularly for the challenging banana-to-maize transfer scenario. The model demonstrated particular robustness to variations in image quality, which poses a common challenge in field-collected data. When tested on images with simulated noise, motion blur, and lighting variations, accuracy degradation was only 3.8% compared to 12.4% for ResNet-50 and 9.2% for EfficientNet. This robustness stems from the meta-learning training regime, which exposed the model to diverse augmentations during meta-training, and the neuro-fuzzy system's inherent tolerance to input uncertainty.

Severity Class	Precision (%)	Recall (%)	F1-Score (%)	Mean Absolute Error in % Area
No Disease (0%)	99.1	98.7	98.9	0.8
Trace (1-10%)	94.3	92.8	93.5	2.1
Light (11-20%)	93.8	94.2	94.0	3.4
Moderate (21-49%)	95.6	96.1	95.8	4.7
Severe (50-100%)	97.2	97.8	97.5	5.0
<b>Weighted Average</b>	<b>96.8</b>	<b>96.5</b>	<b>96.6</b>	<b>3.2</b>

**TABLE 15: Disease severity classification performance**

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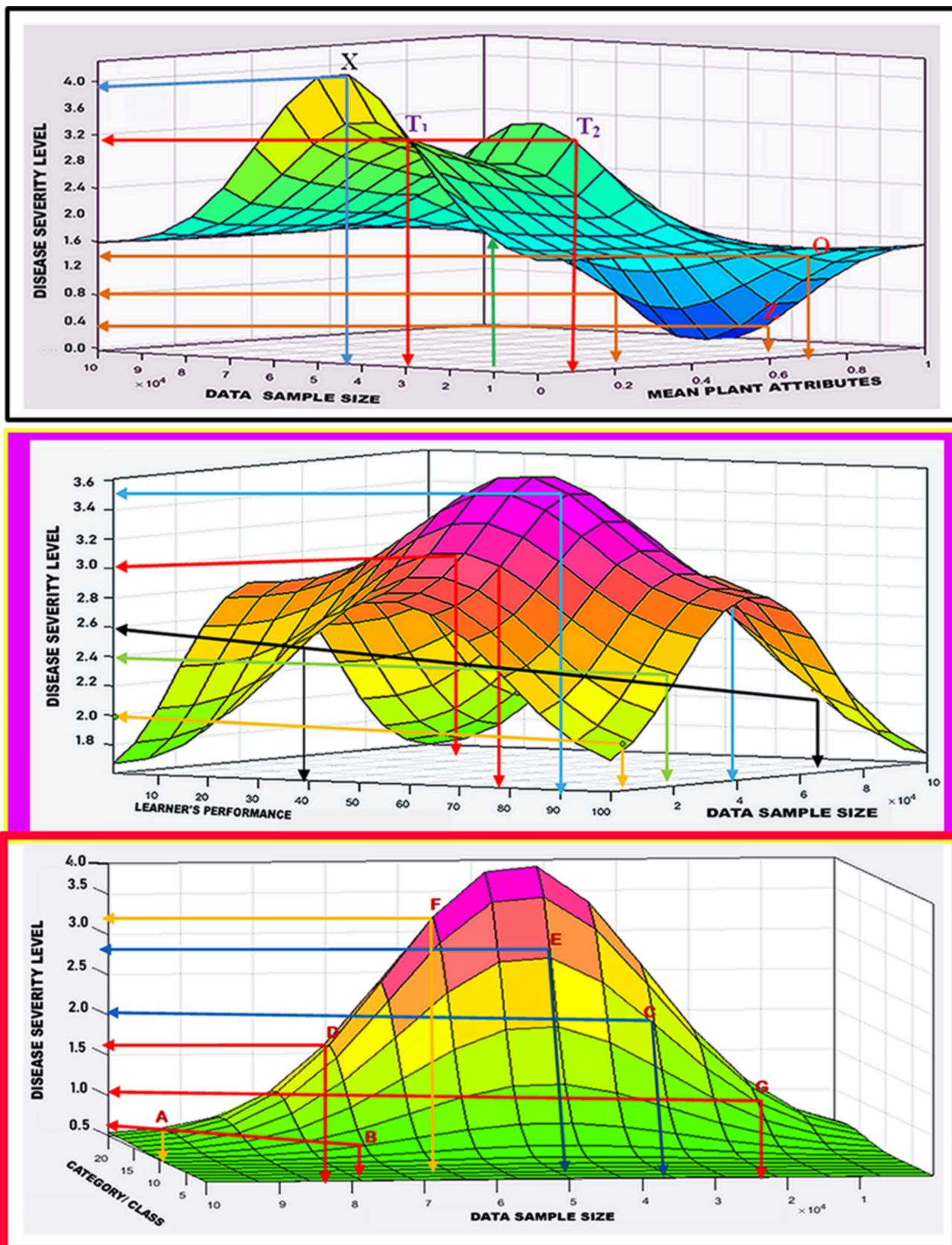


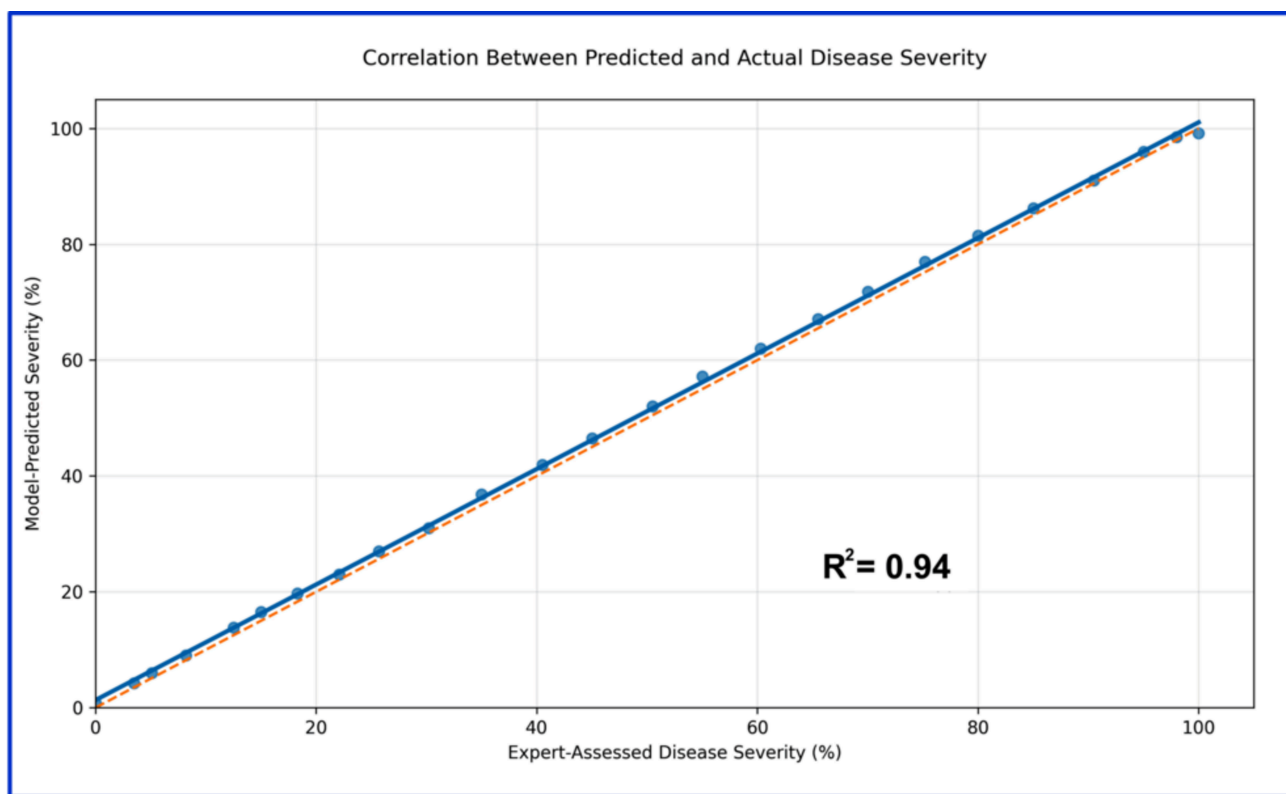
FIGURE 12: Disease severity prediction chart

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Training Crops	Test Crop	Developed Model Accuracy	Fine-tuned ResNet-50 Accuracy	Improvement
Cassava + Maize	Banana	98.9%	84.2%	+14.7%
Cassava + Banana	Maize	99.5%	86.7%	+13.8%
Maize + Banana	Cassava	99.0%	88.9%	+10.1%
<b>Average</b>	-	<b>99.1%</b>	<b>86.6%</b>	<b>+12.5%</b>

**TABLE 16: Cross-crop generalization performance**



**FIGURE 13: Correlation between predicted and expert-assessed disease severity**

Furthermore, the model demonstrated strong performance across different plant growth stages, with accuracy varying by less than 2.5% between early-, mid-, and late-stage images. This temporal stability, a significant improvement over the 10-15% variation typical of previous methods, is crucial for monitoring disease progression throughout the growing season. The effectiveness of the neuro-fuzzy-enhanced meta-learning model is further supported by its robust foundational architecture: the neural network emerged as the most reliable base learner, achieving an AUC of 99.7% and accuracy, F1-score, precision, and recall consistently above 91%. Analysis also revealed crop-dependent specialization, with KNN performing best for cassava, random forest for maize (97.54% average accuracy), and KNN again for banana (99.96%

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accuracy). Interpreting the model's internal decision logic, feature interaction analysis confirmed that diagnostic accuracy is significantly enhanced by high-resolution imagery, which provides optimal high-quality features. The model exhibited stable, adaptive reasoning across varying severity scores and input qualities, dynamically leveraging higher-performing learners to adjust parameters when subtle attribute variations were detected. This capacity to synthesize knowledge from an ensemble of learners underscores the system's robustness and its ability to produce reliable outputs even when individual components underperform.

### Limitations and future research directions

Several constraints warrant consideration, which in turn delineate clear pathways for future research. The model's performance is bounded by the current dataset scope, which, while substantial, does not encompass the full global diversity of crops and diseases or extreme field conditions, necessitating expanded validation efforts. While the utilized dataset of 51,000 images spans three countries and includes variations in lighting, background, and image capture devices, it remains limited in its geographical and environmental coverage. The model's performance in agroecological zones not represented in the training data such as temperate regions, high-altitude environments, or areas with different soil and climate conditions requires further validation. Additionally, disease symptom expression can vary significantly based on local cultivars, farming practices, and environmental factors not fully captured in our current dataset.

Furthermore, the computational cost of meta-training may pose a barrier to initial development, suggesting a need for efficient model distillation techniques. Although, the model achieves efficient inference suitable for edge deployment (620 ms on Raspberry Pi 4), the meta-training process itself requires substantial computational resources (48 hours on NVIDIA RTX 3090). A subtle interpretability-performance trade-off was also observed in edge cases, where rule-based formulations can oversimplify complex symptom patterns. To address these limitations and extend the system's capabilities, promising research directions include multimodal integration, incorporating hyperspectral, weather, and soil data via advanced fusion architectures for comprehensive risk assessment, the development of a continual learning neuro-fuzzy framework with dynamic rule expansion to enable lifelong adaptation without catastrophic forgetting. Global-scale validation across under-represented regions is also critical to ensure generalizability and guide regional adaptation. Incorporating enhanced explainability through visualization techniques, such as saliency maps, could further strengthen human-AI collaboration. By pursuing these directions, the next generation of diagnostic tools can become more robust, universally applicable, and seamlessly integrated into the global agricultural knowledge ecosystem. Future work should also prioritize large-scale validation across more diverse agricultural environments, including temperate regions (Europe, North America), semi-arid zones (Sub-Saharan Africa), and high-altitude farming systems (Andes, Himalayas). Collaborations with agricultural research stations in these regions should be established to collect representative datasets and evaluate model performance under local conditions.

## Conclusions

This paper presents a novel meta-learning framework that integrates efficient SqueezeNet embeddings with interpretable neuro-fuzzy inference for plant disease diagnosis. The primary contributions include a model that achieves an optimal balance between near-perfect accuracy (99.9%), parameter efficiency (4.8M), and explainability, while enabling rapid few-shot adaptation to novel diseases. Key experimental findings demonstrate superior performance in classification, robust cross-crop generalization (99.1%), precise severity assessment ( $R^2 = 0.94$ ), and practical feasibility for deployment on edge devices. The neuro-fuzzy component proved essential for managing diagnostic uncertainty and providing human-readable rules, directly addressing trust barriers in real-world adoption. This work offers a practical, explainable, and adaptable tool for automated plant disease diagnosis. By advancing the integration of meta-learning with explainable AI principles, it contributes directly to the development of accessible technologies for sustainable crop protection and global food security.

## Appendices

### Dataset information

The collected plant disease datasets utilized for this study are provided and available below:

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1. Cassava plant dataset titled "Makerere University Cassava Image Dataset" is available at <https://doi.org/10.7910/DVN/T4RB0B>
2. Banana plant dataset titled "PSFD-Musa DATASET" is available at <https://data.mendeley.com/datasets/4wyymrcpyz/1>
3. Maize plant dataset titled "Diseases of maize in the field" is available at <https://doi.org/10.25403/UPresearchdata.20237613>

The combined and pre-processed data from these three sources formed the foundational corpus for training, validation, and testing the proposed neuro-fuzzy-enhanced meta-learning model, as reported in the results section.

## Additional Information

### Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

**Concept and design:** Femi T. Johnson, Adebukola Onashoga , Adebayo Abayomi-Alli, Adejimi Alaba

**Acquisition, analysis, or interpretation of data:** Femi T. Johnson, Adebukola Onashoga , Adebayo Abayomi-Alli, Adejimi Alaba

**Drafting of the manuscript:** Femi T. Johnson, Adebukola Onashoga , Adebayo Abayomi-Alli, Adejimi Alaba

**Critical review of the manuscript for important intellectual content:** Femi T. Johnson, Adebukola Onashoga , Adebayo Abayomi-Alli, Adejimi Alaba

**Supervision:** Femi T. Johnson, Adebukola Onashoga , Adebayo Abayomi-Alli, Adejimi Alaba

### Disclosures

**Human subjects:** All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

### Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request.

## References

1. Onashoga Adebukola S, Johnson Femi T, Ojo Oluwafolake E, Adeniran AI: [A critical review of machine learning models for intelligent plant disease diagnosis](#). Proceedings of the Nigeria Computer Society, International Conference on Communication and E-Systems for Economic Stability (CeSES'2023). 2023, 359- 368.
2. Aanis A, Dharmendra S, Alyel G: [A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools](#). Smart Agricultural Technology. 2023, 3:100083. [10.1016/j.atech.2022.100083](https://doi.org/10.1016/j.atech.2022.100083)
3. Onashoga A, Johnson F, Abayomi-Alli A, Falana O, Ismaila A, Clement A: [Machine learners' performance analysis for meta-learning base classifier selection in plant disease diagnosis](#). Cureus Journal of Computer Science. 2025, 2:es44389-025-03667-5. [10.7759/s44389-025-03667-5](https://doi.org/10.7759/s44389-025-03667-5)
4. Ayu HR, Surtono A, Apriyanto DK: [Deep learning for detection cassava leaf disease](#). Journal of Physics: Conference Series. 2021, 1751:012072. [10.1088/1742-6596/1751/1/012072](https://doi.org/10.1088/1742-6596/1751/1/012072)
5. Chen CC, Ju YB, Tie JL, Christopher CK, Kun CW, Zhen L: [EfficientNet: a low-bandwidth IoT image sensor framework for cassava leaf disease classification](#). Sensors and Materials. 2021, 33:4031-4044. [10.18494/sam.2021.3526](https://doi.org/10.18494/sam.2021.3526)

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6. Chug A, Bhatia A, Singh AP, Singh D: [A novel framework for image-based plant disease detection using hybrid deep learning approach](#). *Soft Computing*. 2022, 27:13613-13638. [10.1007/s00500-022-07177-7](#)
7. Wang S, Xu D, Liang H, et al.: [Advances in deep learning applications for plant disease and pest detection: a review](#). *Remote Sensing*. 2025, 17:698. [10.3390/rs17040698](#)
8. Zeeshan M, Shojaei Baghini M, Pandey A: [EdgePlantNet: Lightweight edge-aware cyber-physical system for plant disease detection using enhanced attention CNNs](#). *Pervasive and Mobile Computing*. 2025, 110:102059. [10.1016/j.pmcj.2025.102059](#)
9. Li L, Wang Y, Xu Y, Lin KY: [Meta-learning based industrial intelligence of feature nearest algorithm selection framework for classification problems](#). *Journal of Manufacturing Systems*. 2022, 62:767-776. [10.1016/j.jmsy.2021.03.007](#)
10. Chen L, Cui X, Li W: [Meta-learning for few-shot plant disease detection](#). *Foods*. 2021, 10:2441. [10.3390/foods10102441](#)
11. Farpat SL, Baviskar DP: [Intelligent multicrop disease detection using adaptive multimodal hybrid deep learning: a comprehensive framework for Indian agricultural systems](#). *International Journal of Environmental Sciences*. 2025, 11:1127-1136. [10.64252/fkard779](#)
12. Sibiya M, Sumbwanyambe M: [Automatic fuzzy logic-based maize common rust disease severity predictions with thresholding and deep learning](#). *Pathogens*. 2021, 10:131. [10.3390/pathogens10020131](#)
13. Onashoga A, Ojesanmi O, Johnson F, Ayo FE: [A fuzzy-based decision support system for soil selection in olericulture](#). *Journal of Agricultural Informatics*. 2018, 9:65-77. [10.17700/jai.2018.9.3.480](#)
14. Kim A, Shahroz M, Alabdullah Z, et al.: [ANFIS fuzzy convolutional neural network model for leaf disease detection](#). *Frontiers in Plant Science*. 2024, 15:1465960. [10.3389/fpls.2024.1465960](#)
15. Ghaus H, Malik MH, Munawar S, Nawaz SA, Aslam T: [Multi-crops leaves diseases classification using fuzzy logic and pre-trained CNN methods](#). *Journal of Computing & Biomedical Informatics*. 2024, 1-13.
16. Adekunle TS, Lawrence MO, Alabi OO, Afolorunso AA, Ebong GN, Oladipupo MA: [Deep learning technique for plant disease detection](#). *Computer Science and Information Technologies*. 2024, 5:55-62. [10.11591/csit.v5i1.p55-62](#)
17. Xu Y, Zhao B, Zhai Y, Chen Q, Zhou Y: [Maize diseases identification method based on multi-scale convolutional global pooling neural network](#). *IEEE Access*. 2021, 9:27959-27970. [10.1109/access.2021.3058267](#)
18. Chen J, Zeb A, Nanekaran YA, Zhang D: [Stacking ensemble model of deep learning for plant disease recognition](#). *Journal of Ambient Intelligence and Humanized Computing*. 2023, 14:12359-12372. [10.1007/s12652-022-04334-6](#)
19. Jakjoud F, Hatim A, Bouaaddi A: [Deep Learning application for plant diseases detection](#). *BDIoT '19: Proceedings of the 4th International Conference on Big Data and Internet of Things*. 2020, 1-6. [10.1145/3372938.3372983](#)
20. Gokulnath BV, Gandhi UD: [RETRACTED ARTICLE: Regularized deep clustering approach for effective categorization of maize diseases](#). *Journal of Ambient Intelligence and Humanized Computing*. 2021, 14:16037-16046. [10.1007/s12652-021-02912-8](#)
21. Zhao H, Yang C, Guo W, Zhang L, Zhang D: [Automatic estimation of crop disease severity levels based on vegetation index normalization](#). *Remote Sensing*. 2020, 12:1930. [10.3390/rs12121930](#)
22. Babu T, Nair RR, Balusamy B, Khoh WH, Nair J: [AgriFewNet—A lightweight RGB few-shot learning model for efficient plant disease classification](#). *Applied Sciences*. 2025, 15:12787. [10.3390/app152312787](#)
23. Clohessy JW, Santosh S, Kelly GB, et al.: [Development of a high-throughput plant disease symptom severity assessment tool using machine learning image analysis and integrated geolocation](#). *Computers and Electronics in Agriculture*. 2021, 184:106089. [10.1016/j.compag.2021.106089](#)

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