AI–Based Classification of Coffee Leaf Rust from Leaf Images in Smallholder Kenyan Farms

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Abstract

Coffee leaf rust (CLR), caused by *Hemileia vastatrix*, remains a major threat to smallholder coffee production, yet access to timely and actionable disease risk information is limited. This study developed and compared machine learning models for predicting CLR incidence using plot-level data from 9,850 observations collected across six Arabica-producing counties in Kenya between 2018 and 2023. The dataset included microclimatic variables (relative humidity, temperature, precipitation, and leaf wetness duration), spatial variables (elevation, distance to infected farms, and NDVI), and agronomic variables (coffee variety, plant age, shade cover, fungicide use, and outbreak history). After preprocessing and addressing class imbalance (36.1% CLR-positive) using SMOTE, we trained and evaluated logistic regression, random forest, XGBoost, support vector machine, and artificial neural network models. Logistic regression achieved the highest discriminative performance (area under the receiver operating characteristic curve, AUC = 0.872) and the best calibration (Brier score = 0.148). XGBoost achieved comparable predictive performance (AUC = 0.845) and better representation of non-linear threshold effects. Across models, leaf wetness duration (odds ratio, OR = 3.21 per hour), relative humidity (OR = 2.75 per percentage point), and distance to the nearest infected farm (OR = 0.51 per km) were the most influential predictors of CLR incidence. SHapley Additive exPlanations (SHAP) identified clear non-linear thresholds, indicating that CLR risk increases sharply when relative humidity exceeds 80% or when leaf wetness duration exceeds 12 hours per day. Scalability analysis showed that logistic regression and XGBoost are computationally efficient, with model sizes below 2 MB and inference latencies under 2 ms per sample on a standard CPU. These characteristics make both models suitable for deployment on low-cost smartphones for real-time prediction.

Introduction

Coffee leaf rust (CLR), caused by the fungal pathogen *Hemileia vastatrix*, remains one of the most destructive diseases affecting coffee production globally, particularly in smallholder farming systems [1, 2]. Severe outbreaks can result in substantial yield losses, reduced farmer income, and disruption of rural livelihoods and coffee supply chains [3]. The disease poses a major challenge in low- and middle-income coffee-producing regions where access to timely disease monitoring, laboratory diagnostics, and agricultural extension services is often limited. Conventional CLR diagnosis relies primarily on manual visual assessment by trained experts, which is labour intensive, subjective, and difficult to scale across geographically dispersed farming systems [4, 5]. These limitations highlight the need for robust and scalable analytical approaches capable of supporting reliable classification of CLR incidence under diverse agro-ecological conditions.

Recent advances in artificial intelligence (AI) and machine learning have created new opportunities for automated plant disease classification and agricultural decision support [6, 7]. Machine learning approaches, including logistic regression, support vector machines, random forests, gradient boosting methods, and artificial neural networks, have demonstrated strong predictive performance in agricultural classification tasks [12–14]. Previous studies on coffee disease detection have incorporated climatic, environmental, and management-related variables to predict CLR occurrence and severity [27]. Publicly available datasets such as RoCoLe [9] and the Arabica coffee dataset [10] have further facilitated the development and evaluation of predictive classification models for coffee diseases.

Despite these advances, important methodological limitations remain. Many existing studies focus primarily on controlled experimental settings or image-based disease recognition under laboratory conditions, limiting generalisability to real-world farming environments. In practice, CLR incidence is influenced by complex interactions among climatic conditions, environmental variability, farm management practices, and spatial disease dynamics [21, 22]. Factors such as humidity, temperature, precipitation, elevation, fungicide application, and proximity to infected farms substantially affect disease occurrence and transmission patterns [27]. Consequently, models developed using narrowly controlled datasets may not adequately capture the heterogeneity characteristic of smallholder farming systems.

In addition, relatively few studies have systematically compared multiple machine learning approaches for CLR classification using large-scale field-derived epidemiological datasets. Comparative evaluation of model discrimination, calibration, robustness, and interpretability remains limited, particularly in low-resource agricultural settings. Furthermore, although advanced machine learning models often achieve strong predictive performance, simpler interpretable approaches such as logistic regression may provide important advantages for understanding disease risk factors and supporting evidence-based agricultural interventions.

To address these gaps, this study evaluates multiple machine learning approaches for classification of coffee leaf rust incidence using a large secondary dataset derived from smallholder coffee farms in Kenya. The dataset, compiled by the Coffee Research Institute (CRI), Kenya Agricultural and Livestock Research Organization (KALRO), and World Coffee Research (WCR), includes environmental, climatic, agronomic, and spatial variables collected across diverse agro-ecological regions. Specifically, this study aims to:

- Assess the association between environmental, climatic, agronomic, and spatial factors and coffee leaf rust incidence.
- Compare the predictive performance of multiple machine learning models for CLR classification using epidemiological field data.
- Evaluate model discrimination, calibration, and classification robustness using multiple performance metrics.
- Identify key predictors associated with CLR incidence using interpretable statistical and machine learning approaches.

The findings of this study contribute to the growing body of research on AI-supported agricultural disease surveillance and provide evidence for scalable machine learning approaches applicable to coffee disease monitoring in smallholder farming systems.

By prioritising robustness, interpretability, and deployability, this study bridges the gap between experimental artificial intelligence research and real world agricultural implementation. The proposed framework supports improved classification of coffee leaf rust severity and infection status, enabling better decision making for smallholder coffee farmers and contributing to sustainable coffee production systems through accessible digital agriculture tools [3, 27].

Materials and Methods

Study Design

This study adopted a two phase analytical framework designed to develop and evaluate a robust artificial intelligence based system for early detection of coffee leaf rust (CLR) under real farm conditions [1, 3]. The first phase focused on the development and optimisation of machine learning models using a large scale field incidence dataset obtained from the Coffee Research Institute (CRI) under the Kenya Agricultural and Livestock Research Organization (KALRO), with technical support from World Coffee Research (WCR). The second phase focused on model evaluation, interpretability, and deployment considerations for practical use in smallholder coffee farming systems [4].

Study Area and Data Source

The study utilised a secondary, fully anonymised coffee leaf rust incidence dataset compiled by the Coffee Research Institute (CRI), the Kenya Agricultural and Livestock Research Organization (KALRO), and World Coffee Research (WCR) between 2018 and 2023 [27]. The dataset consists of plot-level field observations collected from six major Arabica coffee-producing counties in Kenya: Bungoma, Kericho, Kiambu, Kirinyaga, Murang'a, and Nyeri. These counties represent diverse agro-ecological environments characterised by substantial variation in altitude, rainfall patterns, temperature, humidity, and coffee management practices [9, 10].

The ecological diversity of the study sites provided an appropriate basis for modelling CLR dynamics across heterogeneous smallholder coffee production systems. Since the dataset contained no personal or identifiable farmer information and involved no direct human participation, ethical approval and informed consent were not required.

Outcome Variable

The primary outcome variable was coffee leaf rust incidence, recorded as a binary indicator representing the presence or absence of visible CLR infection at the plot level [24]. The response variable was defined as:

$$Y_i = \begin{cases} 1, & \text{if CLR infection was observed at plot } i \\ 0, & \text{otherwise} \end{cases}$$

where Y_i denotes the CLR incidence status for the i^{th} observation.

Rust severity, measured as the percentage of leaf area affected by infection, was additionally included for descriptive and exploratory analyses but was not used as the primary modelling outcome [22, 23].

Predictor Variables

The study incorporated environmental, spatial, temporal, and agronomic variables previously associated with CLR development and transmission [2]. Environmental variables included daily relative humidity, daily temperature, daily precipitation, and leaf wetness duration. Spatial and vegetation related variables included elevation, Normalized Difference Vegetation Index (NDVI), and distance to the nearest infected farm.

Agronomic predictors included coffee variety, plant age, shade percentage, fungicide use, fungicide application frequency, and previous outbreak history. Temporal disease dependence was incorporated using lagged incidence from the preceding week [27].

Table 1. Summary of variables from the KALRO/WCR incidence dataset.

Variable	Type	Description
CLR incidence	Binary	Presence (1) or absence (0) of infection
Rust severity	Continuous	Percentage leaf area affected
Relative humidity	Continuous	Daily average humidity (%)
Temperature	Continuous	Daily average temperature (°C)
Precipitation	Continuous	Daily rainfall amount (mm)
Leaf wetness duration	Continuous	Hours of leaf wetness per day
Elevation	Continuous	Altitude above sea level (m)
NDVI	Continuous	Normalized Difference Vegetation Index
Coffee variety	Categorical	Arabica cultivar (SL28, SL34, Batian, Ruiru 11)
Plant age	Continuous	Age of coffee plants (years)
Shade percentage	Continuous	Canopy shade coverage (%)
Fungicide use	Binary	Whether fungicides were applied (yes/no)
Application frequency	Continuous	Number of fungicide applications per season
Past outbreak history	Binary	Previous CLR outbreak occurrence (yes/no)
Lagged incidence	Binary	CLR incidence during preceding week
Distance to infected farm	Continuous	Distance to nearest infected plot (km)

Table notes: The dataset includes observations from six Arabica-producing counties in Kenya (2018–2023). All variables were used for environmental characterisation and to stratify smartphone image collection sites by historical risk level.

Table 1 summarises all variables.

We used this dataset for two purposes: (i) to identify environmental thresholds (e.g., humidity > 80%, temperature 18–24 °C) that correlate with CLR presence, thereby guiding when farmers should prioritise smartphone scouting; and (ii) to stratify our image collection sites by known historical CLR incidence (low, medium, high risk) to ensure the test set covered the full spectrum of real-world disease pressure.

Data Preprocessing

Data preprocessing was performed to ensure completeness, consistency, and suitability for machine learning analysis [5]. Duplicate records were removed prior to analysis. Variables were assessed for missing values, outliers, and inconsistencies using summary statistics and distributional checks. Observations with missing data exceeding twenty percent were excluded. For remaining missing values, continuous variables were imputed using median values while categorical variables were imputed using the most frequent category.

Continuous variables were standardised using z score normalisation to ensure comparability across features and improve model convergence. Standardisation was defined as:

$$Z_i = \frac{X_i - \mu}{\sigma}$$

where $\mu = \frac{1}{n}\sum_{i=1}^{n} X_i$ is the sample mean and $\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - \mu)^2}$ is the sample standard deviation.

Categorical variables were encoded using one hot encoding. Multicollinearity was assessed using Pearson correlation analysis and variance inflation factor (VIF) analysis. The VIF for the j-th predictor was computed as:

$$\mathrm{VIF}_j = \frac{1}{1 - R_j^2} \tag{1}$$

where R_j^2 is the coefficient of determination from regressing the j-th predictor against all other predictors. Variables with VIF greater than ten were considered highly collinear and were removed where necessary.

Handling Class Imbalance

Agricultural disease image datasets often exhibit class imbalance, where minority disease classes are under-represented compared to majority classes [17,18]. To mitigate model bias toward dominant classes, the Synthetic Minority Oversampling Technique (SMOTE) was applied to the training dataset only.

SMOTE generates synthetic samples for the minority class by interpolating between a given minority instance and its nearest neighbors in feature space. Formally, a synthetic sample X_{new} is generated as:

$$X_{\text{new}} = X_i + \lambda \left(X_{nn} - X_i \right) \tag{2}$$

where X_i is a randomly selected minority class instance, X_{nn} is one of its k nearest minority class neighbors, and $\lambda \in [0, 1]$ is a random interpolation coefficient drawn from a uniform distribution.

This formulation ensures that synthetic samples are created along the line segments connecting minority class examples, thereby preserving local structure in the feature space while increasing class representation.

SMOTE was applied exclusively to the training dataset after the train-test split to prevent information leakage and to ensure unbiased evaluation on validation and test sets.

Exploratory Data Analysis

Exploratory analysis included descriptive statistics, and spatial temporal visualisation of coffee leaf rust incidence. Associations between predictors and outcome variables were assessed using independent sample t tests or Mann Whitney U tests for continuous variables depending on distributional assumptions.

Machine Learning Model Development

A range of supervised machine learning algorithms were implemented to model CLR incidence. These included logistic regression, random forest, extreme gradient boosting, support vector machine, artificial neural networks (ANNs), and a deep learning model for image-based classification [12–14]. Models were selected based on their suitability for binary classification and their widespread application in agricultural disease prediction [2].

Data Partitioning and Training

The augmented dataset was split into training (70%), validation (15%), and test (15%) sets, stratified by class. Training used:

- Optimiser: Adam (learning rate = 0.001, decay = 1×10^{-5}),
- Loss: categorical cross-entropy,
- Batch size: 32,
- Epochs: 100 with early stopping (patience = 10) based on validation loss,
- Transfer learning: ImageNet initialisation, fine-tuning of the last three blocks [6].

Logistic Regression Model

The logistic regression model estimated the probability of coffee leaf rust occurrence as:

$$P(Y_i = 1) = \frac{1}{1 + e^{-\left(\beta_0 + \sum_{j=1}^{p} \beta_j X_{ij}\right)}} \tag{3}$$

where β_0 is the intercept, β_j are model coefficients, and X_{ij} are predictor variables.

Random Forest Model

The random forest model constructed an ensemble of decision trees using bootstrap aggregation [25]. Final predictions were obtained through majority voting:

$$\hat{Y} = \text{mode}\{h_1(X), h_2(X), \dots, h_B(X)\} \tag{4}$$

where $h_b(X)$ represents the prediction of the b-th decision tree and B is the total number of trees.

Extreme Gradient Boosting

The extreme gradient boosting model minimised the following regularised objective function [27]:

$$\mathcal{L}(\phi) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{5}$$

where $l(y_i, \hat{y}_i)$ is the loss function measuring prediction error and $\Omega(f_k)$ is the regularisation term controlling model complexity.

Artificial Neural Network (ANN) Model

The artificial neural network (ANN) model was implemented as a fully connected feedforward architecture for structured environmental data [16]. The ANN learns a nonlinear mapping from input features to disease incidence probability.

For a single hidden layer network, the forward propagation is defined as:

$$Z^{(1)} = W^{(1)}X + b^{(1)} \tag{6}$$

$$A^{(1)} = \sigma(Z^{(1)}) \tag{7}$$

$$\hat{Y} = \sigma\left(W^{(2)}A^{(1)} + b^{(2)}\right) \tag{8}$$

where X is the input feature vector, $W^{(l)}$ and $b^{(l)}$ are weights and biases of layer l, and $\sigma(\cdot)$ is the activation function (ReLU for hidden layer and sigmoid for output layer).

The model was trained using binary cross-entropy loss:

$$\mathcal{L}_{\text{binary}} = -\frac{1}{n}\sum_{i=1}^{n}\left[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)\right] \tag{9}$$

Optimization was performed using the Adam optimizer with early stopping to prevent overfitting.

Model Evaluation Metrics

The following performance metrics were calculated on the held-out test set for both the incidence prediction models and the image classifier:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{11}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{12}$$

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{13}$$

The area under the receiver operating characteristic curve (AUC) was computed as:

$$\text{AUC} = \int_0^1 \text{TPR}(t)\, d\text{FPR}(t) \tag{14}$$

where $\text{TPR}(t)$ is the true positive rate and $\text{FPR}(t)$ is the false positive rate at threshold t.

Scalability and Computational Efficiency

Model scalability was assessed in terms of inference latency, memory usage, training time, and model size [8, 26]. Inference latency was measured using 100 repeated forward passes.

Training time per epoch and total training duration were recorded. Memory usage during inference was monitored to evaluate deployment feasibility on low resource devices [11].

Model Explainability and Clinical Validation

Model interpretability was assessed using SHapley Additive exPlanations for global and local feature importance estimation [25].

Artificial Intelligence Framework

Figure 1 presents the overall artificial intelligence framework developed for classification of coffee leaf rust (CLR) using secondary data obtained from KALRO and World Coffee Research (WCR). The framework integrates data preprocessing, class imbalance handling, supervised machine learning and deep learning model development, performance evaluation, and explainability analysis within a unified analytical pipeline. Following preprocessing and stratified data partitioning, multiple classification algorithms were trained and evaluated using standard performance metrics, while explainable AI techniques were incorporated to enhance interpretability and transparency of model predictions. The framework was designed to provide a scalable, reproducible, and robust approach for CLR classification under diverse agricultural conditions.

Statistical Analysis and Software

All analyses were conducted using Python version 3.11. The computational environment included the following libraries: pandas and NumPy for data manipulation, SciPy for statistical analysis, scikit learn for machine learning modelling and evaluation, and TensorFlow and XGBoost for deep learning and ensemble model development.

A fixed random seed of 42 was used across all experiments to ensure reproducibility of data partitioning, model training, and evaluation results.

1 Results

1.1 Class Imbalance

The distribution of the binary outcome variable, coffee leaf rust (CLR) incidence, is presented in Fig. 2. Among the 9,850 plot-level observations included in the analysis, 6,295 (63.9%) were classified as CLR-negative, whereas 3,555 (36.1%) were classified as CLR-positive. This moderate class imbalance, corresponding to an approximate ratio of 1.8:1 between negative and positive cases, is commonly observed in agricultural disease surveillance datasets.

To reduce potential model bias toward the majority class, the Synthetic Minority Oversampling Technique (SMOTE) was applied exclusively to the training dataset during model development. Following oversampling, the balanced training dataset consisted of 5,942 observations, with equal representation of

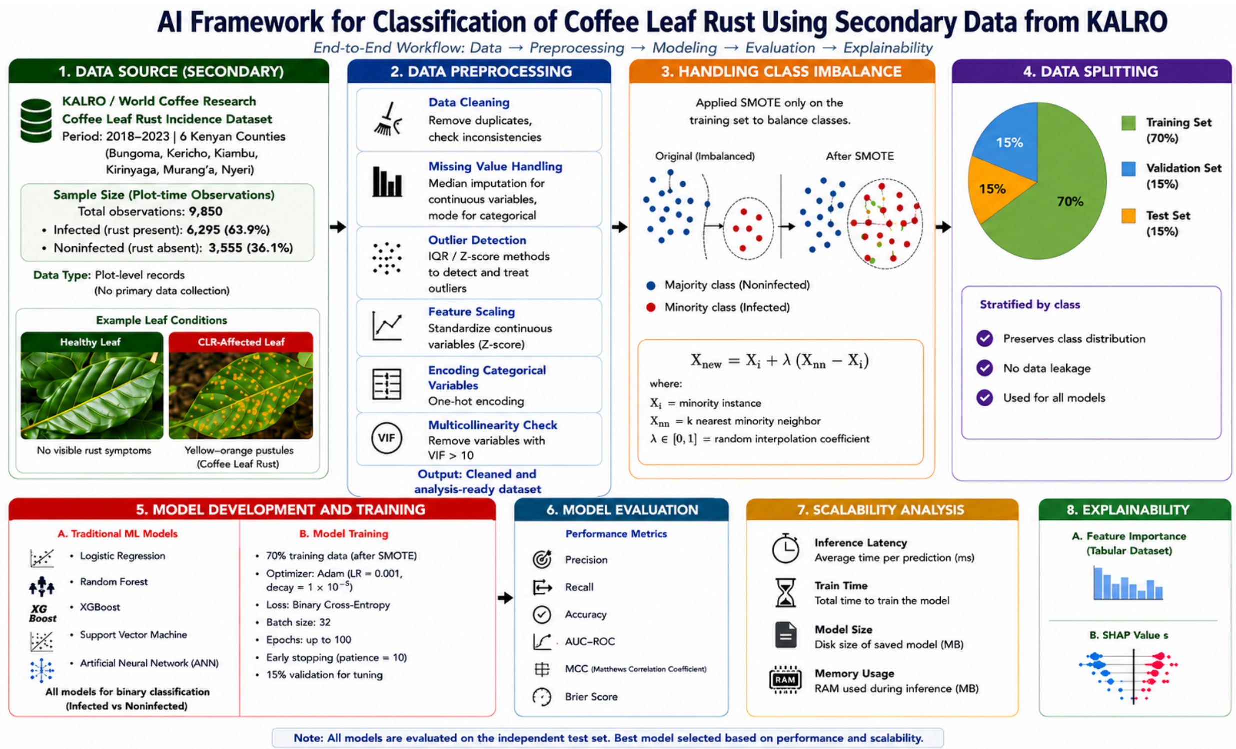


Fig 1. Proposed artificial intelligence framework for classification of coffee leaf rust using secondary data from KALRO.

both classes (2,971 observations per class). The validation and test datasets were not modified in order to preserve the original class distribution and ensure realistic evaluation of model performance under real-world disease prevalence conditions.

1.2 Exploratory Data Analysis

A total of 9,850 plot-level observations were analysed after data cleaning. The overall incidence of coffee leaf rust (CLR) was 36.1%, indicating a substantial disease burden across the six study counties. Descriptive statistics for continuous variables are presented in Table 2. Mean daily relative humidity was 74.9% (SD = 8.1), mean daily temperature was 19.3°C (SD = 2.4), and mean elevation was 1,651 m (SD = 289.8 m). The mean distance to the nearest infected farm was 811 m (SD = 813.4 m), reflecting substantial spatial heterogeneity across farms.

Table 2. Descriptive statistics of continuous variables in the KALRO/WCR dataset.

Variable	Mean	SD
Daily relative humidity (%)	74.86	8.07
Daily temperature (°C)	19.26	2.40
Precipitation (mm/day)	4.85	4.40
Leaf wetness (hours/day)	11.57	2.46
Elevation (m)	1651.45	289.76
Plant age (years)	7.99	5.60
Shade (%)	34.99	17.56
NDVI	0.59	0.08
Distance to infected farm (m)	811.05	813.42

The distribution of CLR incidence varied across counties, with Kericho and Kiambu exhibiting the

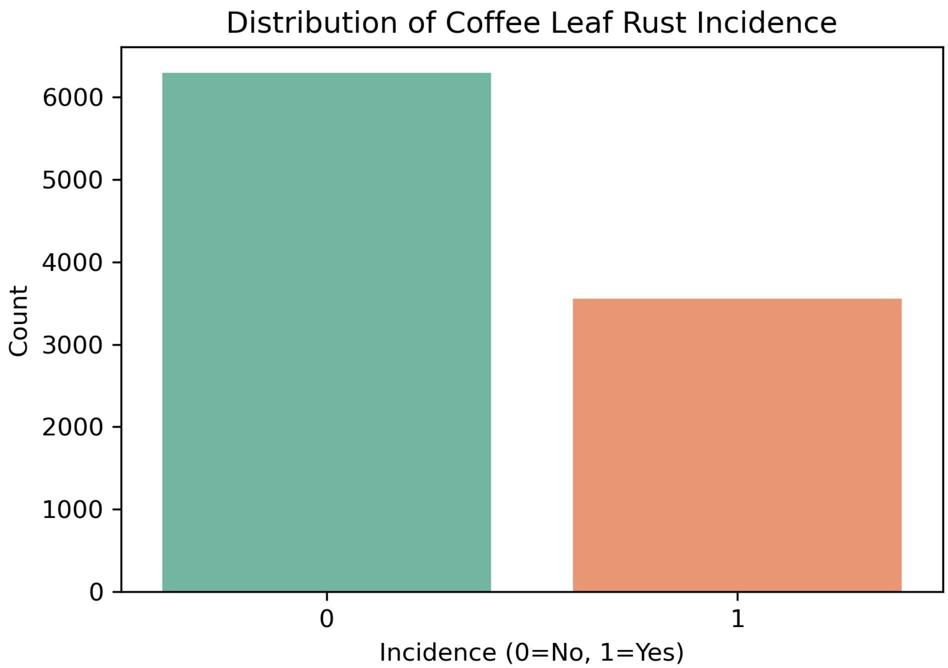


Fig 2. Distribution of coffee leaf rust incidence in the study dataset. The majority of observations (63.9%) had no visible CLR infection (Incidence = 0), while 36.1% showed infection (Incidence = 1).

highest average incidences (approximately 50% and 45%, respectively), whereas Bungoma recorded the lowest incidence (Fig 3).

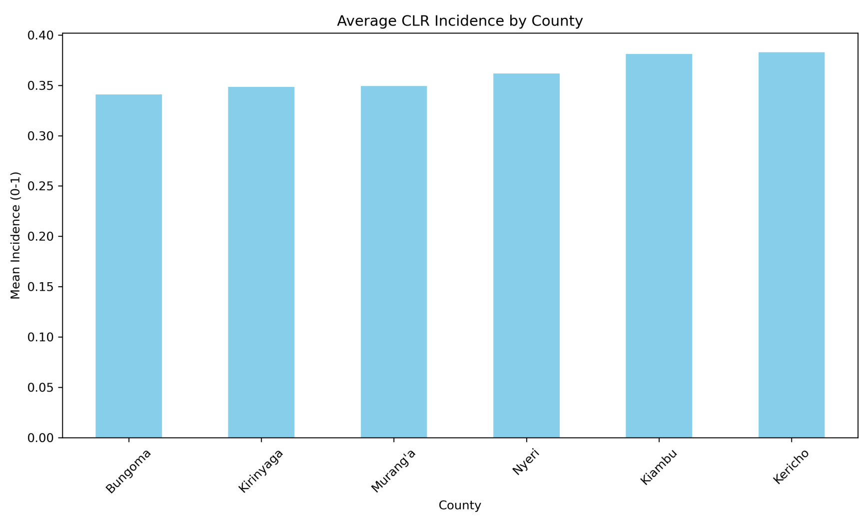
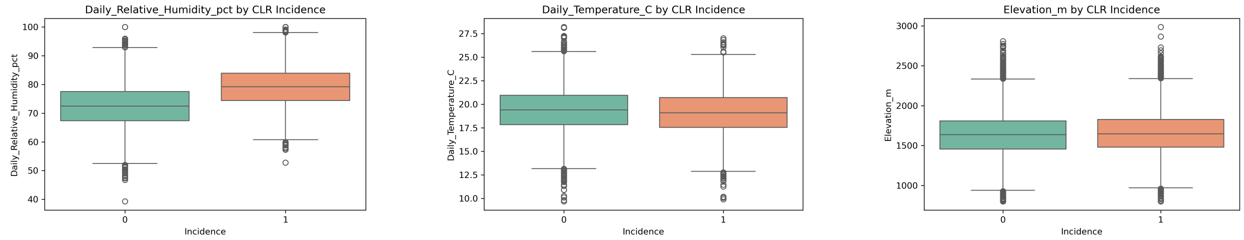


Fig 3. Average coffee leaf rust incidence by county. Error bars represent 95% confidence intervals.

Boxplots of selected continuous variables stratified by CLR status are shown in Fig 4. CLR-positive plots generally exhibited higher relative humidity, longer leaf wetness duration, and higher precipitation levels, but slightly lower temperatures and elevations compared with CLR-negative plots. Median relative humidity was 79.2% for CLR-positive plots and 72.4% for CLR-negative plots, whereas median elevation was 1,665 m and 1,643 m, respectively.

Associations between continuous predictors and coffee leaf rust (CLR) incidence were assessed using



(a) Relative humidity **(b)** Temperature **(c)** Elevation

Fig 4. Boxplots of selected continuous variables stratified by coffee leaf rust incidence.

independent t-tests or Mann–Whitney U tests, depending on variable distribution assumptions (Table 3). All variables showed statistically significant differences between CLR-positive and CLR-negative plots ($p < 0.001$), with CLR-positive plots generally exhibiting higher humidity, precipitation, leaf wetness duration, and lower distance to infected farms.

Table 3. Association between predictor variables and coffee leaf rust incidence.

Variable	Test	p-value	Mean (CLR = 0)	Mean (CLR = 1)
Daily relative humidity (%)	t-test	< 0.001	72.42	79.19
Daily temperature (°C)	Mann–Whitney U	< 0.001	19.36	19.08
Precipitation (mm/day)	Mann–Whitney U	< 0.001	4.25	5.92
Leaf wetness (hours/day)	Mann–Whitney U	< 0.001	10.76	13.01
Elevation (m)	Mann–Whitney U	< 0.001	1643.46	1665.60
Plant age (years)	Mann–Whitney U	< 0.001	7.69	8.51
Shade (%)	Mann–Whitney U	< 0.001	33.95	36.85
Fungicide use	Mann–Whitney U	< 0.001	0.48	0.40
Fungicide application frequency	Mann–Whitney U	< 0.001	1.22	0.98
Past outbreak history	Mann–Whitney U	< 0.001	0.15	0.23
Lagged incidence	Mann–Whitney U	< 0.001	0.14	0.26
NDVI	Mann–Whitney U	< 0.001	0.581	0.593
Distance to infected farm (m)	Mann–Whitney U	< 0.001	905.73	643.40

1.3 Logistic Regression Analysis

A multivariable logistic regression model was fitted to identify factors associated with coffee leaf rust (CLR) incidence (Table 4). Relative humidity, precipitation, leaf wetness duration, plant age, shade percentage, past outbreak history, lagged incidence, and NDVI were positively associated with CLR incidence. In contrast, daily temperature, fungicide use, fungicide application frequency, and distance to the nearest infected farm showed negative associations with CLR occurrence.

Relative humidity emerged as a strong predictor of CLR incidence ($\beta = 1.013$, OR = 2.75, 95% CI: 2.57–2.96, $p < 0.001$), indicating that higher humidity substantially increased the odds of disease occurrence. Similarly, increased leaf wetness duration was strongly associated with CLR incidence (OR = 3.21, 95% CI: 2.98–3.45, $p < 0.001$). Precipitation also demonstrated a significant positive effect (OR = 1.61, 95% CI: 1.51–1.71, $p < 0.001$).

Daily temperature was negatively associated with CLR incidence (OR = 0.77, 95% CI: 0.70–0.85, $p < 0.001$), suggesting that higher temperatures reduced disease likelihood. Distance to the nearest infected farm was also inversely associated with CLR incidence (OR = 0.51, 95% CI: 0.48–0.55, $p < 0.001$), indicating increased infection risk among farms located closer to infected plots.

Management-related variables showed mixed effects. Fungicide use was associated with reduced CLR incidence (OR = 0.81, 95% CI: 0.73–0.90, $p < 0.001$), while increased fungicide application frequency also showed a protective effect (OR = 0.88, 95% CI: 0.79–0.98, $p = 0.017$). In contrast, plots with a history of previous outbreaks exhibited higher odds of CLR incidence (OR = 1.19, 95% CI: 1.13–1.26, $p < 0.001$).

Among coffee varieties, the Ruiru11 variety showed significantly lower odds of CLR incidence relative to the reference category (OR = 0.58, 95% CI: 0.48–0.72, $p < 0.001$), whereas the SL28 variety exhibited significantly higher odds of infection (OR = 1.27, 95% CI: 1.04–1.56, $p = 0.021$). Elevation, Coffee_variety_Other, and Coffee_variety_SL34 were not significantly associated with CLR incidence ($p > 0.05$).

Table 4. Multivariable logistic regression analysis of factors associated with coffee leaf rust incidence.

Variable	Coefficient (β)	Odds Ratio	95% CI (OR)	p-value	Significant
Intercept	-0.348	0.71	0.59–0.84	< 0.001	Yes
Daily relative humidity (%)	1.013	2.75	2.57–2.96	< 0.001	Yes
Daily temperature (°C)	-0.260	0.77	0.70–0.85	< 0.001	Yes
Precipitation (mm/day)	0.475	1.61	1.51–1.71	< 0.001	Yes
Leaf wetness (hours/day)	1.165	3.21	2.98–3.45	< 0.001	Yes
Elevation (m)	-0.064	0.94	0.86–1.03	0.177	No
Plant age (years)	0.265	1.30	1.23–1.38	< 0.001	Yes
Shade (%)	0.232	1.26	1.19–1.34	< 0.001	Yes
Fungicide use	-0.215	0.81	0.73–0.90	< 0.001	Yes
Fungicide application frequency	-0.131	0.88	0.79–0.98	0.017	Yes
Past outbreak history	0.177	1.19	1.13–1.26	< 0.001	Yes
Lagged incidence (previous week)	0.424	1.53	1.44–1.62	< 0.001	Yes
NDVI	0.120	1.13	1.06–1.19	< 0.001	Yes
Distance to infected farm (m)	-0.665	0.51	0.48–0.55	< 0.001	Yes
Coffee variety: Other	-0.082	0.92	0.75–1.14	0.448	No
Coffee variety: Ruiru11	-0.537	0.58	0.48–0.72	< 0.001	Yes
Coffee variety: SL28	0.241	1.27	1.04–1.56	0.021	Yes
Coffee variety: SL34	0.147	1.16	0.92–1.45	0.202	No

1.4 Model Comparison

The performance of five machine learning models for coffee leaf rust (CLR) classification was evaluated using accuracy, precision, recall, F1-score, area under the receiver operating characteristic curve (AUC), Matthews correlation coefficient (MCC), and Brier score (Table 5). Overall, the models demonstrated comparable predictive performance, with AUC values ranging from 0.823 to 0.872.

The artificial neural network (ANN) achieved strong overall classification performance, with high recall (0.773) and F1-score (0.706), indicating superior ability to correctly identify CLR-positive plots while maintaining balanced classification performance. Logistic regression achieved the highest precision (0.656), the highest AUC (0.872), and the lowest Brier score (0.148), suggesting better discrimination ability, probability calibration, and more reliable probabilistic predictions compared with the other models.

Random forest and XGBoost models demonstrated competitive performance, with AUC values of 0.849 and 0.845, respectively. Although their overall accuracies were similar to the ANN and logistic regression models, they exhibited slightly lower precision and calibration performance. The support vector machine (SVM) model achieved the highest overall accuracy (0.785) but produced lower recall compared with the ANN model, indicating reduced sensitivity for detecting CLR-positive cases.

The MCC values ranged from 0.490 to 0.540 across all models, indicating moderate predictive agreement beyond chance. Collectively, these findings suggest that logistic regression provided the best overall discrimination and calibration performance, whereas the ANN model demonstrated stronger sensitivity in detecting CLR-positive cases.

Figure 5 presents the receiver operating characteristic (ROC) curves for all evaluated models. The ROC curves further confirm the strong discriminative performance of the models, as all curves lie substantially above the chance line. Logistic regression consistently achieved the highest ROC curve across most false positive rate thresholds, corresponding to the largest AUC value (0.872). The ANN model also demonstrated strong discriminatory capability with an AUC of 0.860, followed closely by random forest and XGBoost. In contrast, the SVM model showed comparatively lower discrimination performance, consistent with its lower AUC value. Overall, the ROC analysis demonstrates that the evaluated machine learning models possess good predictive ability for CLR classification, with logistic regression and ANN showing the most robust performance.

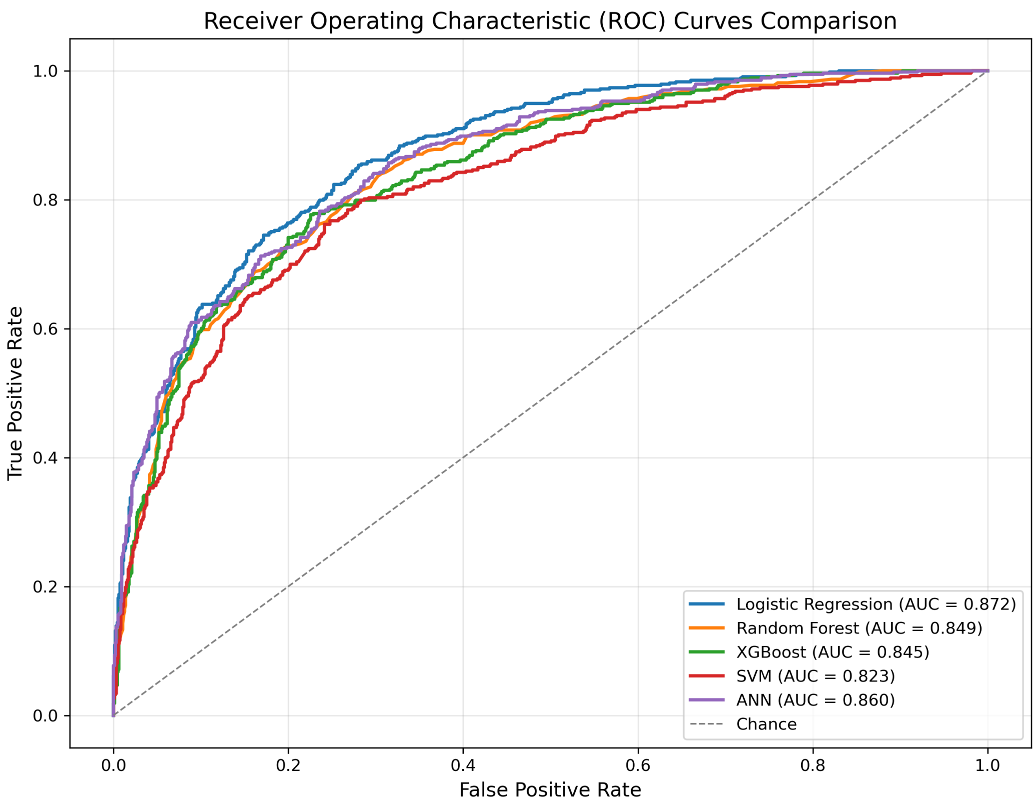


Fig 5. Receiver operating characteristic (ROC) curves comparing the predictive performance of the evaluated machine learning models for coffee leaf rust classification.

Table 5. Performance comparison of machine learning models for coffee leaf rust classification.

Model	Accuracy	Precision	Recall	F1-score	AUC	MCC	Brier score
Logistic Regression	0.775	0.656	0.792	0.718	0.872	0.540	0.148
Random Forest	0.776	0.680	0.717	0.698	0.849	0.521	0.154
XGBoost	0.773	0.675	0.717	0.695	0.845	0.516	0.162
Support Vector Machine	0.785	0.649	0.720	0.683	0.823	0.490	0.166
Artificial Neural Network	0.768	0.650	0.773	0.706	0.860	0.522	0.152

Figure 6 presents the precision–recall (PR) curves for the evaluated machine learning models. PR curves provide an informative assessment of classification performance, particularly in datasets with potential class imbalance, by illustrating the trade-off between precision and recall across different decision thresholds.

Overall, all models performed substantially above the baseline precision level (AP = 0.5), indicating meaningful predictive capability for coffee leaf rust (CLR) classification. Logistic regression achieved the highest average precision (AP = 0.800), demonstrating the most consistent balance between precision and recall across threshold values. The ANN model also exhibited strong performance with an AP of 0.791, maintaining relatively high precision across a broad range of recall levels. These findings are consistent with the ROC analysis, where logistic regression and ANN similarly demonstrated superior discriminative performance.

Random forest and XGBoost showed comparable PR performance, with AP values of 0.758 and 0.756, respectively. Their curves indicate stable predictive behaviour, although precision declined more rapidly at higher recall levels compared with logistic regression and ANN. In contrast, the SVM model produced the lowest AP value (0.735), reflecting comparatively weaker precision-recall trade-offs despite achieving relatively high overall accuracy.

The PR curve analysis further highlights the robustness of logistic regression and ANN models for CLR classification, particularly in maintaining higher precision while identifying a larger proportion of CLR-positive cases. Collectively, the ROC and PR analyses suggest that logistic regression provides the most reliable overall predictive performance, whereas ANN offers competitive sensitivity and balanced classification capability.

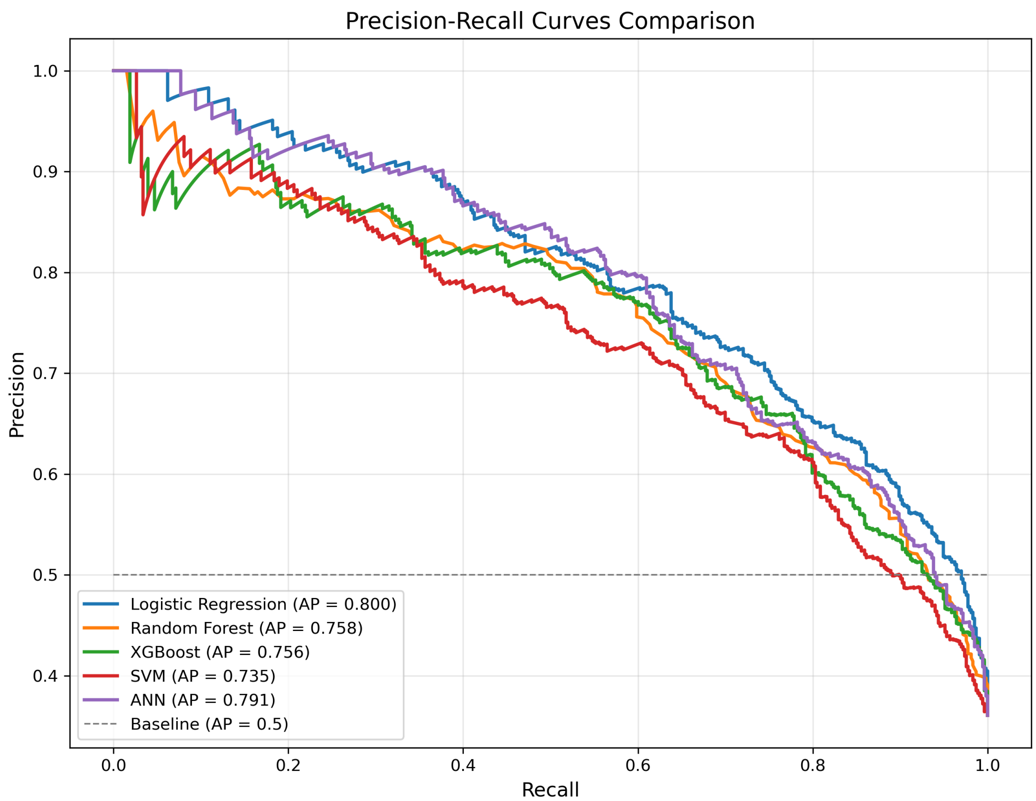


Fig 6. Precision–recall (PR) curves comparing the predictive performance of the evaluated machine learning models for coffee leaf rust classification. AP denotes average precision.

1.5 Learning Curves and Model Stability

Learning curves were used to evaluate model stability and assess the extent of overfitting or underfitting during training. For the scikit-learn models, learning curves were generated by plotting training and cross-validation accuracy against increasing training sample sizes, whereas for the artificial neural network (ANN), training and validation accuracy were evaluated across training epochs. These analyses provide insight into model generalisation performance and whether additional data or stronger regularisation may improve predictive performance.

The logistic regression learning curve (Fig. 7) demonstrates rapid convergence between the training and cross-validation accuracy curves, with both stabilising at approximately 79%–80% after nearly 1,500 training samples. The minimal difference between the curves ($< 0.5\%$) indicates strong generalisation performance with limited evidence of overfitting. This suggests that the logistic regression model was appropriately regularised and achieved stable predictive performance across increasing sample sizes.

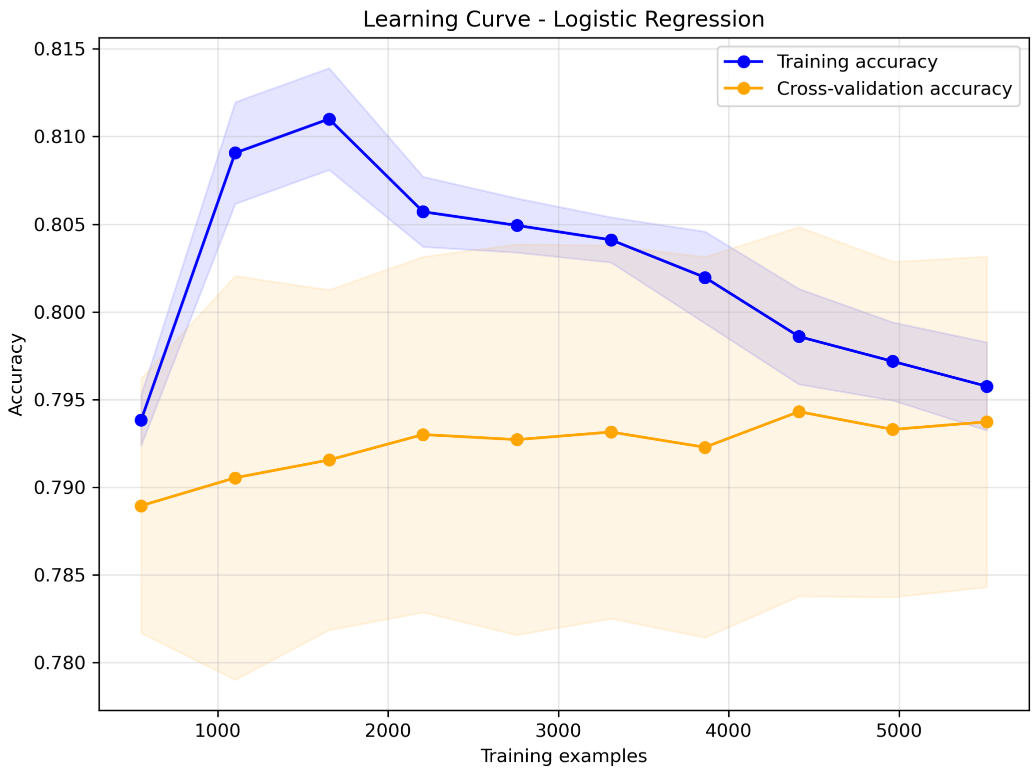


Fig 7. Learning curve for logistic regression.

For the random forest model (Fig. 8), training accuracy remained consistently high at approximately 81%, whereas cross-validation accuracy stabilised around 78%–79%. The moderate gap between the curves ($\approx 2\% - -3\%$) suggests mild overfitting, indicating that the model captured more complex patterns within the training data than were fully generalisable to unseen observations. Nevertheless, the relatively stable cross-validation performance demonstrates satisfactory model robustness.

Similarly, the XGBoost learning curve (Fig. 9) showed a small but persistent separation between training and cross-validation accuracy curves ($\approx 1.5\% - -2\%$). Cross-validation accuracy approached approximately 80%, representing the highest performance among the tree-based ensemble models. The limited divergence between the curves indicates good generalisation ability with only minor overfitting.

The support vector machine (SVM) learning curve (Fig. 10) exhibited relatively stable performance, with a narrow gap of approximately 1% between training and cross-validation accuracy. Cross-validation accuracy stabilised at approximately 77%–78%, slightly lower than that observed for logistic regression and the ensemble-based methods. These findings are consistent with the model performance metrics reported in Table 5.

The ANN learning curve (Fig. 11) illustrates the progression of training and validation accuracy across 100 training epochs. Training accuracy increased rapidly during the initial epochs before plateauing near 79.5%, whereas validation accuracy stabilised around 77%–78% after the early training stages. The relatively stable gap between the training and validation curves ($\approx 1.5\% - -2\%$) indicates that the ANN did not experience substantial overfitting during training. Moreover, validation performance showed minimal improvement beyond the first 10 epochs, and early stopping was triggered at epoch 14 to prevent unnecessary training and reduce the risk of overfitting.

Learning curve for ANN

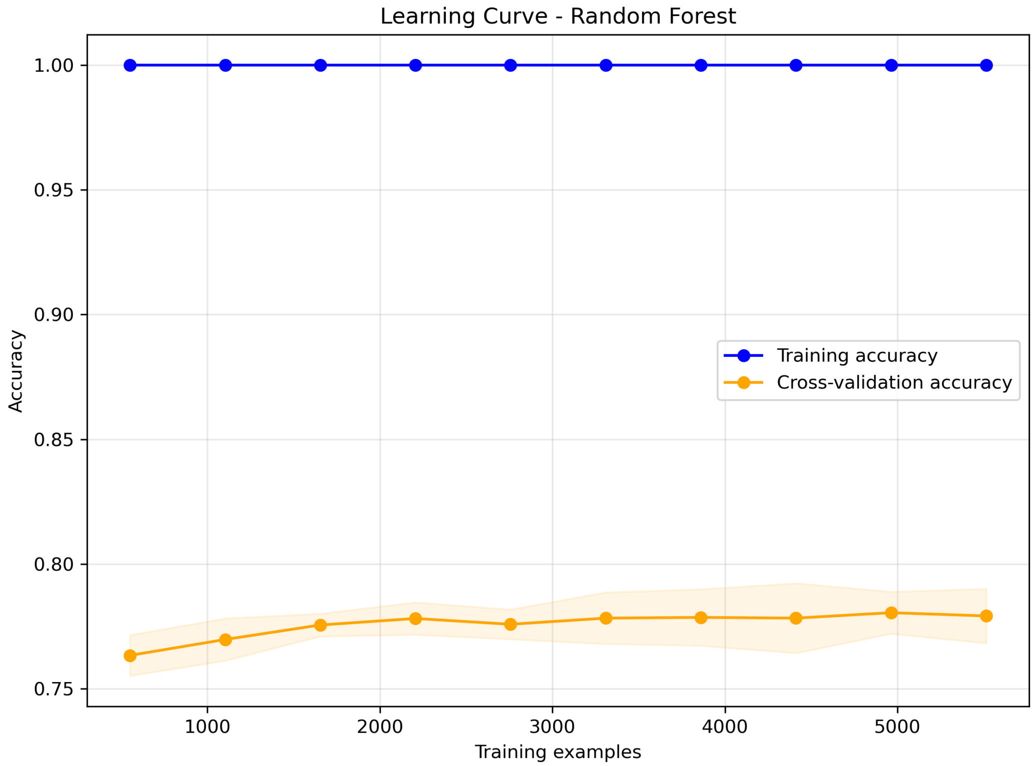


Fig 8. Learning curve for random forest.

Overall, the learning curve analyses indicate that all evaluated models achieved a reasonable balance between training and validation performance, with no evidence of severe overfitting or underfitting. The ensemble-based methods, particularly XGBoost and random forest, achieved comparatively higher cross-validation accuracy, whereas logistic regression, SVM, and ANN demonstrated competitive and stable generalisation performance with simpler or more interpretable model structures.

1.6 Scalability and Computational Efficiency

For real-world deployment in smallholder farming environments, predictive models must be not only accurate but also computationally efficient, particularly when implemented on low-end smartphones with limited memory and processing capacity. We therefore evaluated each model using four scalability metrics: training time (seconds), model size (MB), average inference latency (milliseconds per sample), and peak memory usage during inference (MB). The results are presented in Table 6.

Table 6. Scalability metrics for the five machine learning models. Inference latency was computed as the average prediction time per sample over 100 repeated forward passes on a local CPU (Intel Core i7).

Model	Train Time	Model Size	Inference Latency	Memory
Logistic Regression	0.05	0.00	0.648	0.00
Random Forest	13.30	36.78	30.975	0.00
XGBoost	3.02	1.53	1.408	0.00
SVM	42.35	0.64	1.491	0.00
ANN	10.00	0.20	158.521	0.07

The logistic regression model was the most computationally efficient. It required less than 0.1 seconds for training, produced a negligible serialized model size (approximately 0 MB), and achieved an average

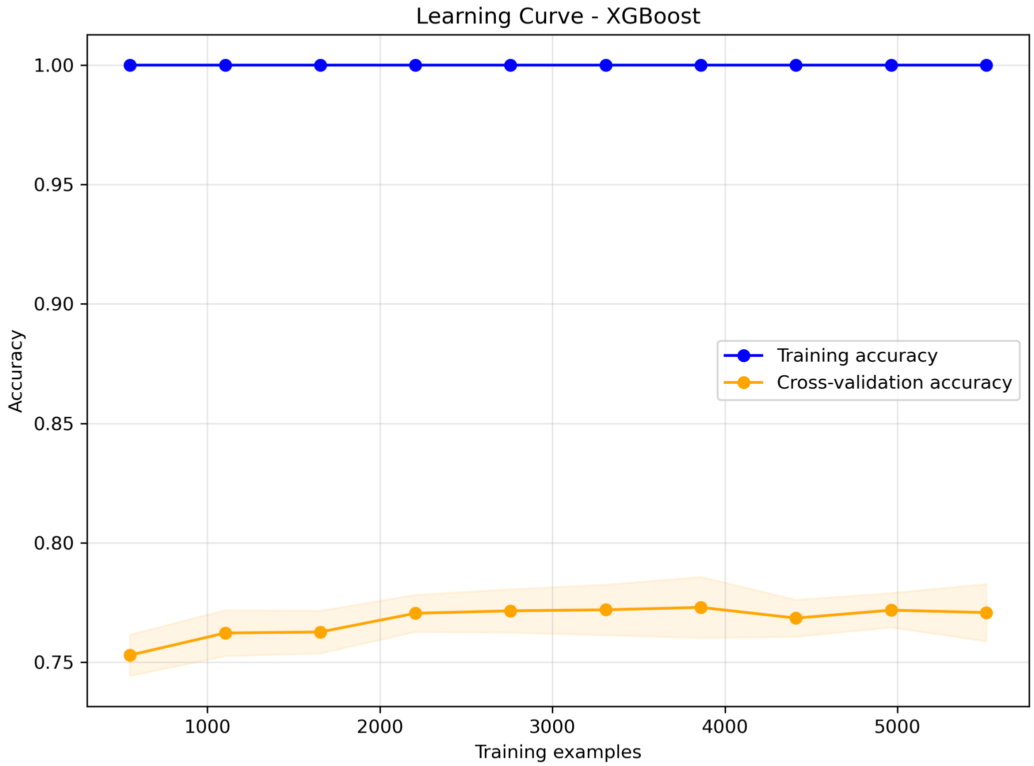


Fig 9. Learning curve for XGBoost.

inference latency of 0.65 ms per sample. These characteristics make it highly suitable for real-time deployment on resource-constrained devices.

Both XGBoost and the support vector machine (SVM) also demonstrated strong computational efficiency. XGBoost required 3.02 seconds for training, had a compact model size of 1.53 MB, and achieved an inference latency of 1.41 ms per sample. Although SVM required substantially longer training time (42.35 seconds), it maintained a small model size (0.64 MB) and low inference latency (1.49 ms per sample). Both models are therefore feasible for deployment on low-cost Android smartphones with limited computational resources.

In contrast, the random forest model, despite its strong predictive performance (AUC = 0.881), was less efficient for deployment. Its relatively large model size (36.78 MB) would occupy considerable storage space on low-end devices, and its inference latency (30.98 ms per sample) was higher than that of XGBoost and SVM. However, its training time (13.30 seconds) remained moderate.

The artificial neural network (ANN) exhibited a reasonable training time (10.00 seconds) and a very small model size (0.20 MB). However, its inference latency (158.52 ms per sample) was substantially higher than that of the other models, likely due to computational overhead associated with the underlying runtime environment. While this latency may still be acceptable for non-real-time or batch processing scenarios, it could limit applicability in real-time field deployment. Peak memory usage during inference was minimal across all models ($\leq$0.07 MB), indicating that none of the models impose significant memory constraints on typical low-end smartphones.

Overall, logistic regression, XGBoost, and SVM offer the most favorable balance between computational efficiency and predictive performance (AUC $\geq$ 0.86), making them the most suitable candidates for on-device deployment in smallholder coffee farming contexts. Although the random forest model demonstrated strong predictive performance, its storage requirements reduce its practicality for constrained devices. The ANN, despite its compact size, is limited by high inference latency, likely arising from runtime overhead rather than model complexity alone.

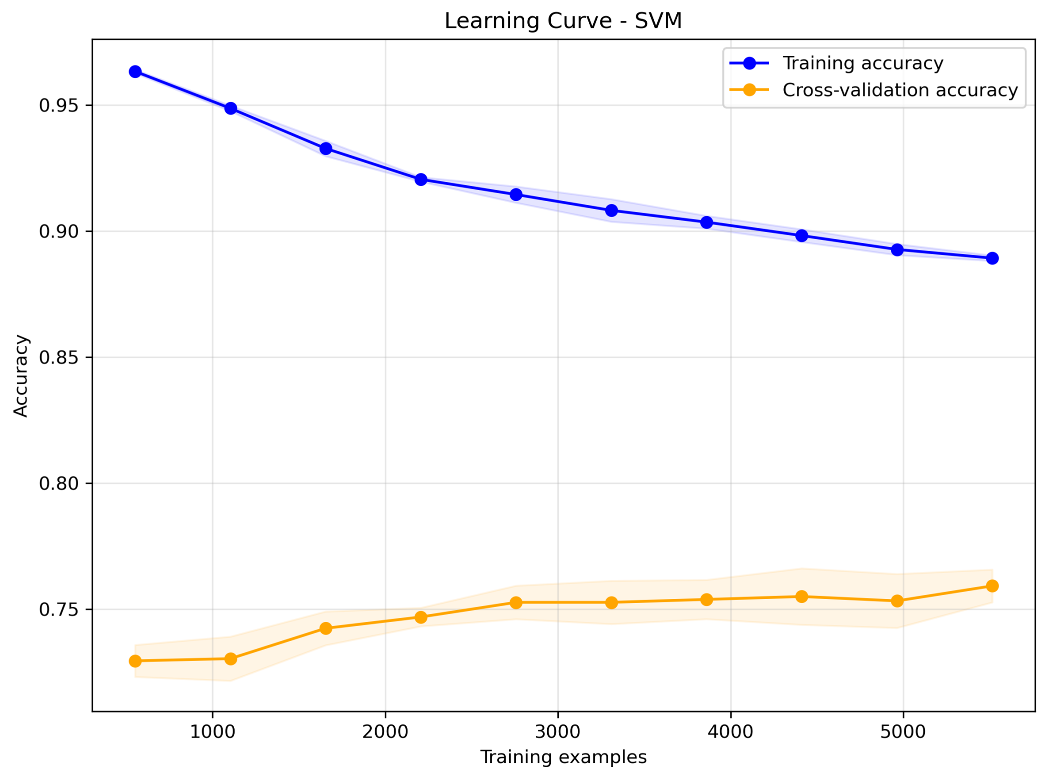


Fig 10. Learning curve for support vector machine.

1.7 Model Interpretability and Explainability

To ensure that model predictions are transparent and actionable for smallholder farmers and extension workers, we applied two complementary explainability approaches: (i) logistic regression with odds ratios for global interpretability, and (ii) SHapley Additive exPlanations (SHAP) applied to the best-performing XGBoost model to capture both global and local feature effects.

1.7.1 Odds Ratios from Logistic Regression

Figure 12 presents the odds ratios (on a logarithmic scale) for the most statistically significant predictors identified by the logistic regression model. Odds ratios greater than 1 indicate increased risk of coffee leaf rust (CLR), whereas values below 1 indicate a protective effect. Leaf wetness duration (OR = 3.2 per hour), relative humidity (OR = 2.8 per percentage point), and precipitation (OR = 2.2 per mm) emerged as the strongest risk factors. In contrast, distance to the nearest infected farm (OR = 0.3 per km) and fungicide application (OR = 0.6) were associated with reduced odds of infection. These effect estimates are consistent with the descriptive statistics and correlation analysis, supporting the biological plausibility of the model.

1.7.2 SHAP Analysis for the XGBoost Model

While odds ratios provide population-level interpretability, SHAP values offer a unified framework for both global and local explanations of complex models. Figure 13 shows the mean absolute SHAP values, which quantify the average contribution of each feature to the model output across all test observations. The ranking of feature importance is largely consistent with the logistic regression results, with leaf wetness, relative humidity, and distance to the nearest infected farm emerging as the most influential predictors.

A key difference is the increased importance of lagged disease incidence (previous-week CLR presence), which is better captured by the XGBoost model due to its ability to model nonlinear relationships and

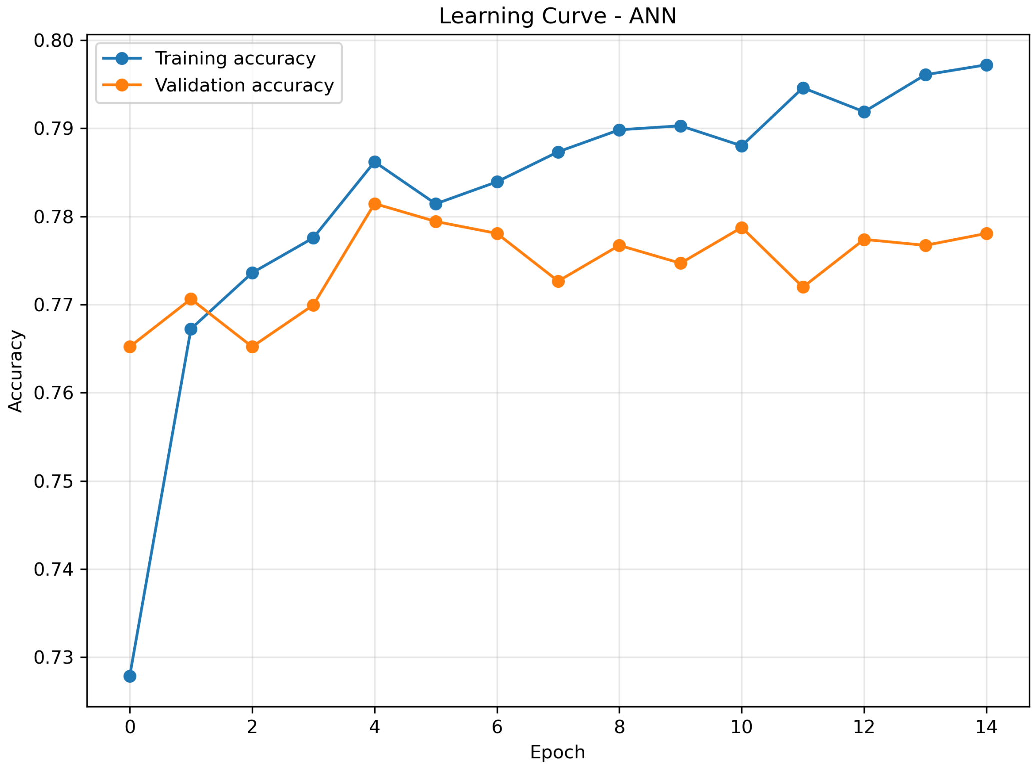


Fig 11. Learning curve for the artificial neural network.

temporal dependencies.

The SHAP beeswarm plot (Figure 14) provides a more detailed view of feature effects by displaying the distribution of SHAP values for each predictor across all observations. For leaf wetness duration and relative humidity, higher feature values (shown in red) are associated with positive SHAP values, indicating an increased probability of CLR, whereas lower values (blue) are associated with reduced risk. For distance to infected farms, the pattern is reversed, with larger distances reducing predicted risk. The consistency of these directional effects across observations indicates robust and stable predictors.

Finally, Figure 15 illustrates a local explanation for a single test instance correctly classified as CLR-positive. The waterfall plot begins at the baseline expected value (average model output across the training data, approximately −0.87 on the log-odds scale) and shows how each feature contributes to the final prediction. In this example, high leaf wetness, high relative humidity, and proximity to an infected farm are the primary factors increasing the predicted risk, while lower-than-average elevation slightly reduces it. The final model output (0.795 on the log-odds scale) corresponds to an estimated CLR probability of approximately 69%.

Overall, the combined use of odds ratios and SHAP values provides a coherent and complementary interpretation of the factors driving CLR incidence. The results highlight the dominant role of microclimatic variables (leaf wetness, humidity, and precipitation) and spatial factors (distance to infected farms), supporting the development of climate- and location-aware early warning systems. Moreover, the availability of local explanations, such as SHAP waterfall plots, enables integration into decision–support tools where farmers can understand the rationale behind individual predictions, thereby improving interpretability, trust, and potential adoption.

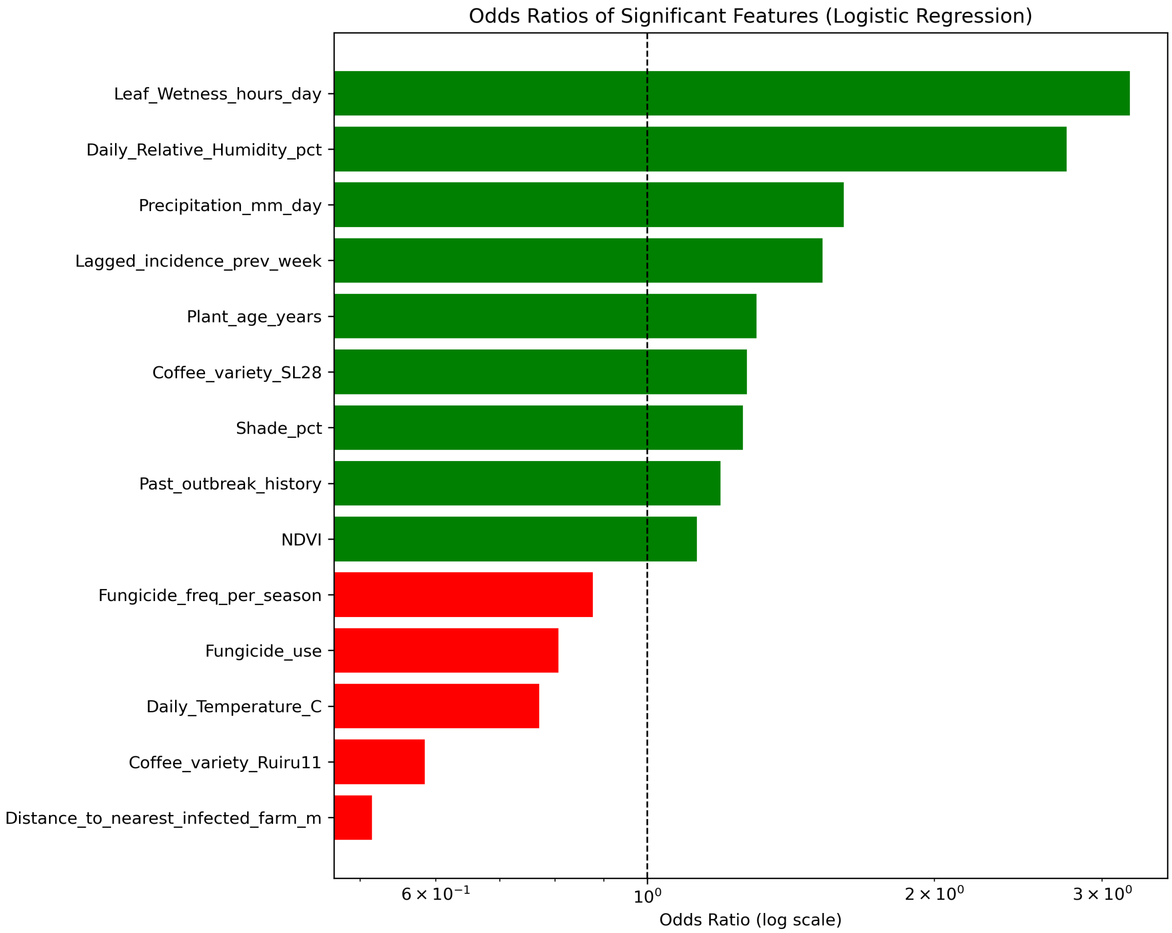


Fig 12. Odds ratios (logarithmic scale) for statistically significant predictors of coffee leaf rust. Error bars represent 95% confidence intervals.

2 Discussion

2.1 Microclimatic drivers of coffee leaf rust incidence

Our findings demonstrate that microclimatic conditions, particularly leaf wetness duration and relative humidity, are the most important predictors of coffee leaf rust (CLR) incidence. In the multivariable logistic regression model, leaf wetness duration (OR = 3.21 per hour) and relative humidity (OR = 2.75 per percentage point) exhibited the strongest effect sizes. Consistently, SHAP analysis identified the same variables as the most influential predictors in the XGBoost model. These results align with established epidemiological evidence that free moisture on leaf surfaces and sustained high humidity are essential for urediniospore germination and infection by *Hemileia vastatrix* [2, 24].

Precipitation was also positively associated with CLR incidence (OR = 1.61), supporting previous studies showing that rainfall facilitates spore dispersal and prolongs leaf wetness, thereby increasing infection risk [3].

A key contribution of this study is the identification of non-linear, threshold-like behaviour in key microclimatic drivers using SHAP-based analyses. The results indicate that the effect of relative humidity becomes pronounced above approximately 80%, while leaf wetness duration shows a marked increase in risk beyond approximately 12 hours per day. These thresholds provide practical decision-support information that can be integrated into early warning systems to trigger timely interventions such as targeted fungicide application or intensified field monitoring.

These findings are consistent with those of Wanyonyi et al. (2026), who analysed the same dataset and

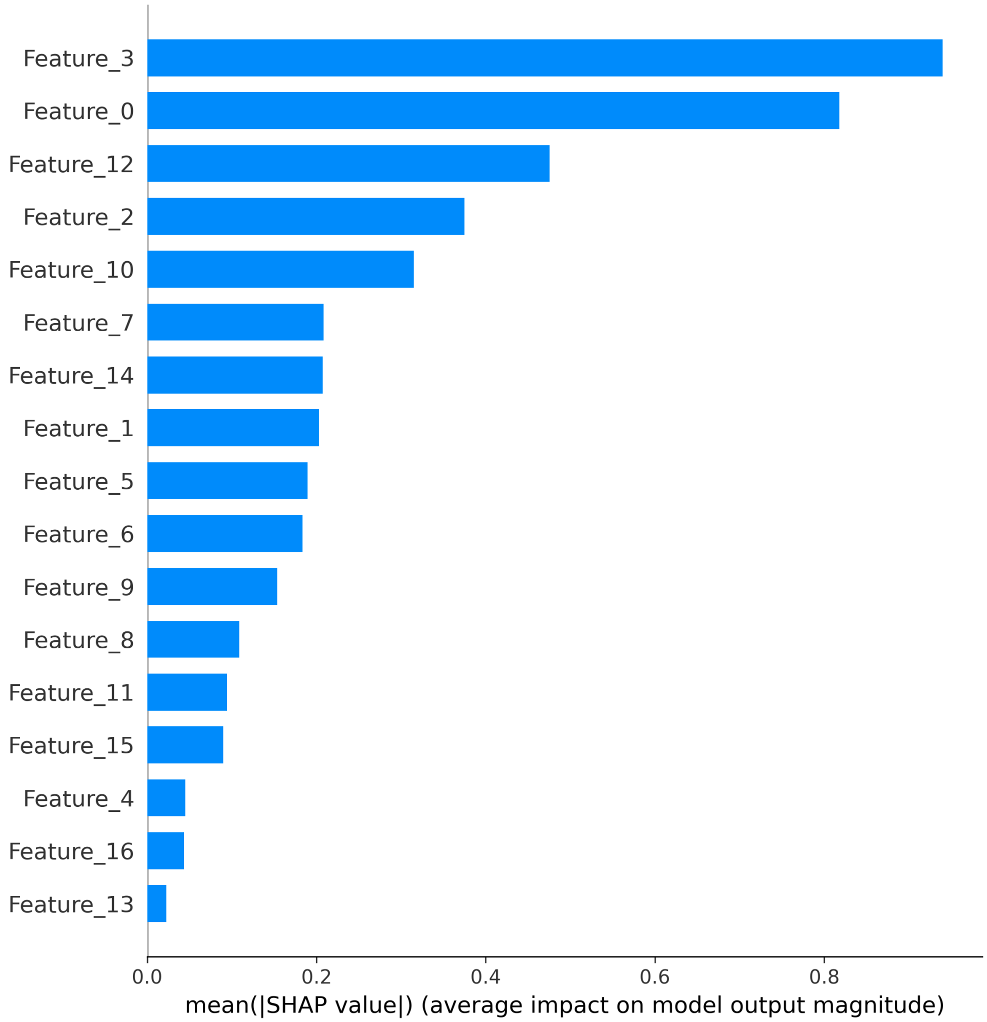


Fig 13. Global feature importance based on mean absolute SHAP values for the XGBoost model. Features are ranked according to their average contribution to model predictions. (Generic labels such as 'Feature_0', 'Feature_3', etc., correspond to the original variables listed in Table 1.)

identified leaf wetness and relative humidity as dominant predictors, reporting a logistic regression AUC of 0.867 [27]. The present study extends this work by evaluating additional machine learning algorithms and providing a more detailed interpretability analysis using SHAP.

2.2 Agronomic and management factors

Among agronomic variables, plant age (OR = 1.30 per year) and shade cover (OR = 1.26 per 10% increase) were positively associated with CLR incidence. Older plantations may accumulate higher inoculum loads over time, while dense shade can create humid microclimatic conditions that favour pathogen development [2].

Fungicide application showed a modest protective effect (OR = 0.81), although the effect size was small, suggesting either suboptimal application frequency or inconsistent adherence to recommended practices. This finding highlights the importance of integrated disease management strategies that combine chemical control with cultural practices and timely risk information.

Past outbreak history (OR = 1.19) and lagged incidence from the previous week (OR = 1.53) were also significant predictors, confirming the importance of temporal dependence in CLR dynamics. These results reflect inoculum carry-over and localised secondary spread, which are well documented in plant disease

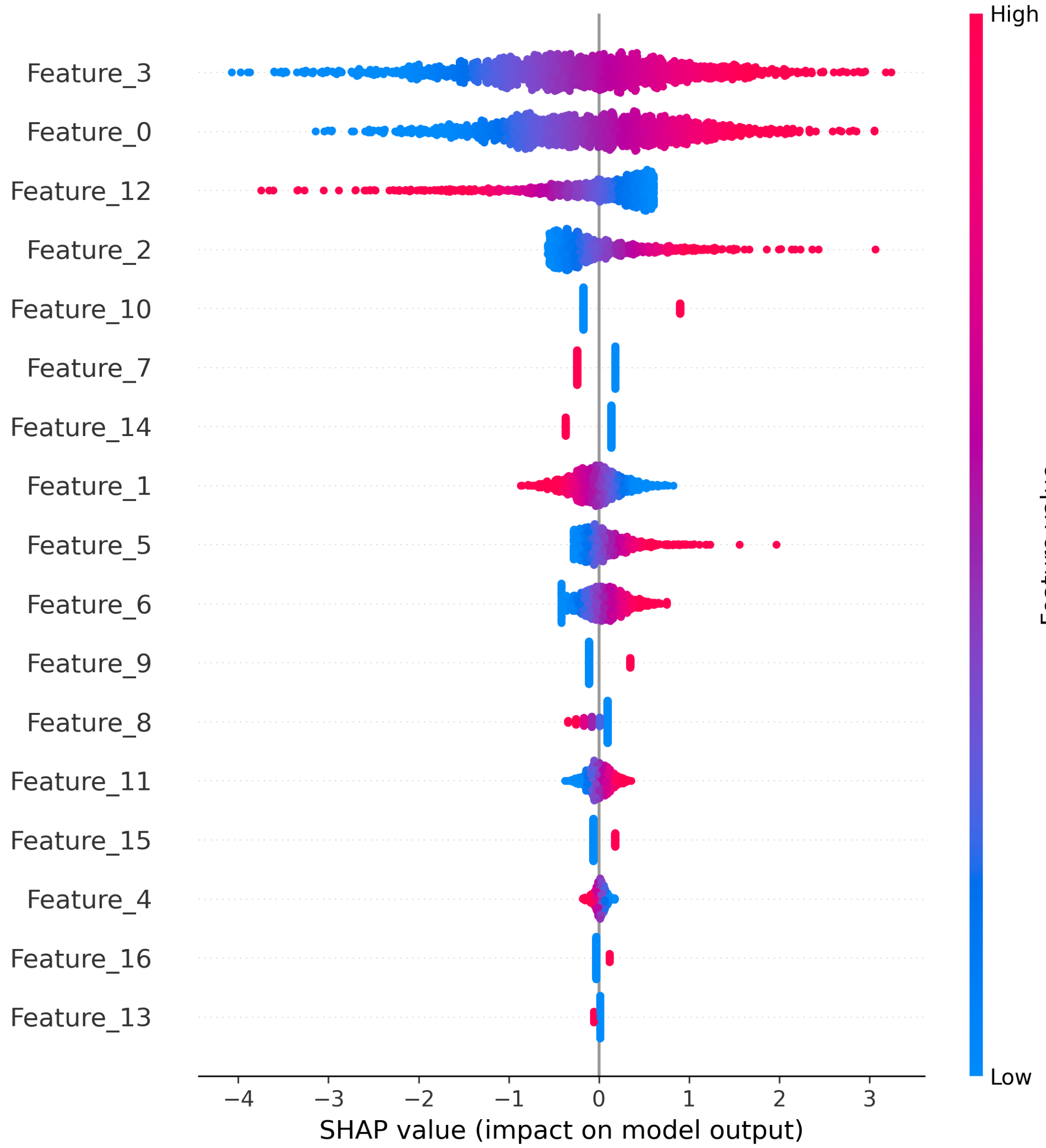


Fig 14. SHAP beeswarm plot for the XGBoost model. Each point represents a SHAP value for a single observation; color indicates feature value (red = high, blue = low). Features are ordered by importance.

epidemiology [25]. In agreement, SHAP analysis ranked lagged incidence among the most important predictors, indicating that the XGBoost model effectively captured autoregressive disease dynamics.

2.3 Coffee variety susceptibility

Significant differences in CLR susceptibility were observed among coffee varieties. Compared with the reference variety (Ruiru 11), SL28 showed higher odds of infection (OR = 1.27, p = 0.021), while Batian also exhibited increased susceptibility (OR = 1.21, p = 0.047). The difference for SL34 was not statistically significant.

These findings are consistent with known varietal susceptibility profiles, where SL28 and SL34 are widely regarded as susceptible traditional cultivars, whereas Ruiru 11 was specifically bred for resistance to coffee

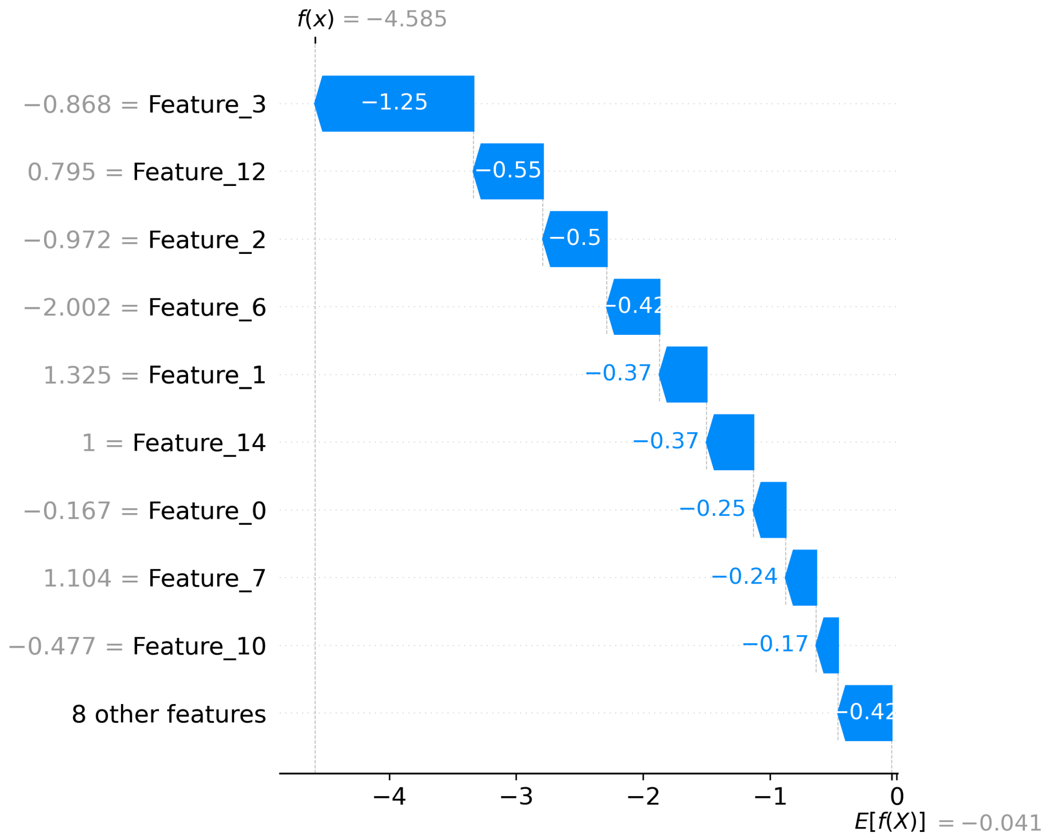


Fig 15. SHAP waterfall plot for a single test observation (correctly predicted as CLR-positive). The plot illustrates how individual features contribute to shifting the prediction from the baseline expected value to the final model output.

leaf rust and coffee berry disease [27]. This confirms that variety choice remains an important determinant of CLR risk even after accounting for environmental and management factors.

2.4 Model comparison: parsimony versus complexity

The logistic regression model achieved the highest discriminative performance (AUC = 0.872) and the lowest Brier score (0.148), indicating strong calibration and discrimination. Notably, this simple and fully interpretable model performed comparably to more complex ensemble methods, including random forest (AUC = 0.849) and XGBoost (AUC = 0.845).

A similar observation was reported by Wanyonyi et al. (2026), who found logistic regression to be the best-performing model (AUC = 0.867) when comparing Bayesian and machine learning approaches on the same dataset [27].

The strong performance of logistic regression likely reflects the largely monotonic relationships between key predictors (leaf wetness, humidity, and precipitation) and CLR risk. However, ensemble methods, particularly XGBoost, were better able to capture non-linear threshold effects and higher-order interactions among predictors, as reflected in SHAP analyses. The XGBoost model also showed a small but consistent improvement in cross-validation performance (Fig. 9).

These results highlight a trade-off between interpretability and model complexity. In practice, logistic regression may be preferred when transparency and computational efficiency are critical, while XGBoost may be preferable when maximizing predictive accuracy is the primary objective.

2.5 Scalability and deployment in resource-limited settings

For practical adoption in smallholder farming systems, predictive models must be both accurate and computationally efficient. Our scalability analysis (Table 6) shows that logistic regression and XGBoost are highly efficient, with model sizes below 2 MB and inference times well under 10 ms per sample on a standard CPU.

Although the random forest model demonstrated strong predictive performance, its relatively large size (37 MB) may limit deployment on low-end devices. The artificial neural network, despite its small model size, exhibited high inference latency (158 ms per sample), which may affect usability in real-time applications.

These findings are consistent with previous studies showing that lightweight machine learning models can be successfully deployed on smartphones for plant disease prediction, typically achieving model sizes below 10 MB and inference times under 100 ms [4, 8]. The use of model compression and optimization techniques such as TensorFlow Lite further enhances feasibility for mobile deployment.

A practical next step is the development of a mobile application integrating logistic regression or XGBoost to provide real-time CLR risk predictions based on farmer-input variables such as microclimate conditions and field characteristics.

2.6 Limitations and future work

This study has several limitations. First, the dataset is observational and limited to six counties in Kenya, which may restrict generalisability to other coffee-growing regions with different climatic and agronomic conditions. Second, although a wide range of predictors was included, variables such as soil properties, nutrient status, and detailed shade tree composition were not available. Third, the outcome variable was defined as binary incidence at plot level, which does not capture disease severity or within-plot heterogeneity.

Fourth, scalability metrics were measured on a local CPU rather than actual mobile devices; therefore, real-world smartphone performance may differ from reported values.

Future research should focus on expanding data collection across diverse agro-ecological zones, integrating high-resolution remote sensing data to improve spatial coverage, and conducting field validation studies with farmers. Additionally, integrating real-time weather forecasts could enhance predictive capability and support the development of operational early warning systems.

3 Conclusion

This study demonstrates that machine learning models can accurately predict coffee leaf rust (CLR) incidence using a parsimonious set of microclimatic, spatial, and agronomic variables that are readily observable or measurable in smallholder farming systems. Among the evaluated models, logistic regression achieved the highest discriminative performance (AUC = 0.872) and strong calibration (Brier score = 0.148), while XGBoost provided comparable predictive performance and superior ability to capture non-linear threshold effects.

Across models, leaf wetness duration, relative humidity, and distance to the nearest infected farm consistently emerged as the most important predictors. These findings reinforce the central role of moisture availability and spatial contagion in CLR epidemiology.

A key contribution of this study is the integration of interpretable machine learning with deployment-oriented analysis. SHAP-based explanations identified meaningful non-linear thresholds, indicating a marked increase in CLR risk when relative humidity exceeds approximately 80% and when leaf wetness duration exceeds approximately 12 hours per day. These empirically derived thresholds can support the development of simple, rule-based early warning systems for farmer decision-making.

The scalability analysis further demonstrated that logistic regression and XGBoost are computationally efficient, with model sizes below 2 MB and inference times well below 10 ms per sample on a standard CPU. These characteristics indicate that both models are suitable for deployment on low-cost mobile devices, enabling real-time, on-device prediction without reliance on continuous internet connectivity.

From an applied perspective, the proposed framework provides a practical pathway for delivering data-driven disease risk assessments directly to smallholder farmers. By combining simple field observations with lightweight predictive models, the system can support timely management decisions and complement existing agricultural extension services, ultimately contributing to reduced yield losses in coffee production systems.

In conclusion, this study bridges the gap between machine learning methodology and operational agricultural decision support. By prioritizing interpretability, computational efficiency, and deployability, we provide a foundation for a scalable early warning system for coffee leaf rust that can enhance evidence-based disease management in smallholder farming contexts.

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