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RING THEORY-BASED AGRICULTURE RISK IDENTIFICATION USING HYBRID MODELS

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ABSTRACT

Unrelenting plant diseases continue to pose a serious challenge to the agricultural sector around the world, undermining the production, food security, and economic stability of people. Conventional control systems are usually not timely assessed on their risks, and they do not consider the intricate element interdependence between environmental, biological, and crop-health components. This study tries to fill these shortcomings by developing a hybrid modelling system enhanced using a ring-theory-based influence mapping to enhance agricultural risk modelling. The research combines various data sets such as field surveys, environmental sensors that are based on the idea of IoT, remote sensing images, and past disease data. Statistical regression, decision trees, random forests, and artificial neural network models were trained as hybrid models simultaneously, optimized by ensemble methods and verified by cross-validation methods and interpretability methods such as SHAP and LIME. Findings indicate that the addition of the ring theory has a considerable positive impact on predictive performance: the accuracy, recall, and AUC-ROC increased by 4.2, 5 points, and 0.05 points, respectively, when compared to the performance of the models that were not augmented using the ring theory. In addition to the predictive gains, the framework provides early-warning signals, informs biosecurity measures, and assists with the development of resistant crops. The work presented in this study can add to the issue of agricultural resilience because it provides a mathematically informed and data-driven solution to the challenge of managing disease risks, which meets the ethical standards of AI and sustainable agriculture.

Keywords: *Agriculture, Risk Identification, Ring Theory, Hybrid Models, Disease Management, Agricultural Resilience*

1. INTRODUCTION

Agriculture contributes to the production of food, fiber, and biofuels, which are key to the sustenance of human life. Nevertheless, the world is still challenged by the persistent occurrence of plant diseases due to fungi, bacteria, viruses, protozoa, insects, and parasitic plants that are still affecting agricultural productivity and quality. Such outbreaks also cause instability in food security and the economy of rural areas as well as reducing the yields. As the world population mounts pressures and climate variations change, disease detection and risk management have been key aspects in the maintenance of sustainable agricultural systems. The traditional methods of disease control, including manual inspection and reactive response, can be characterized by slow response time, lack of accuracy, and predictive strength. Although machine learning (ML) techniques have enhanced the prediction of diseases, they do not always provide a systematic mathematical model of mimicking the interdependence of variables. Consequently, risk assessment is still a piecemeal process that denies the farmer a chance to act proactively to a disease threat. Research Objectives This study aims to: Explore the idea of incorporating ring theory into hybrid ML systems and the possibility of having a stronger foundation for an agricultural risk identification model. Build predictive analysis of multi-source datasets (field surveys, IoT sensors, remote sensing images, and historical data). Design biosecurity measures, resistant crop development plans, and monitoring systems which make use of predictive analytics. Compare the results of the proposed method to that of traditional methods in terms of accuracy, recall, F1-score, and AUC-ROC. Contributions The major findings of this work are as follows: Novel Mathematical Integration: Use of ring theory as a framework of a ring of influence to model interdependencies of crop-health variables and

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environmental variables. Hybrid Modelling Framework: a mixture of classical statistical models with machine learning classifiers (decision trees, random forests, and ANNs) and ensemble learning models. Operational Solutions: Predictive-based resistant crop strategies and biosecurity and early-warning systems. Performance Improvements: Shown accuracy improvements (between 88.3 and 92.7), as well as better recall and AUC-ROC with the addition of ring theory into hybrid models.

2. RELATED WORK

Traditionally, the management of agriculture diseases has been based on manual inspection, chemical treatment, and recommendations by extension services. Visual inspection and field-based survey (Zhao et al., 2025) are common; however, they are subject to human error and small-scale applicability. The use of conventional statistical models, e.g., regression-based predictions, has been used to predict the prevalence of a disease based on climatic and soil variables (Wang et al., 2025). Such techniques however do not always reflect nonlinear interactions or offer real time flexibility.

2.1 Digital technologies and Remote Sensing.

Remote sensing and geospatial analysis were introduced and this made agricultural monitoring much easier. The detection of disease stress signatures among crops using satellite data, UAV-based imaging, and multispectral analysis (Ahmed et al., 2025) has been conducted. These techniques provide high-resolution monitoring, but are costly due to the required hardware and expertise, so are only affordable to smallholder farmers.

2.2 AI-Based and machine learning techniques.

The last several years have seen the use of machine learning (ML) and deep learning (DL) to identify plant diseases. Espejo-Garcia et al. (2025) presented models of foundation vision of the weed condition and disease that enhanced the accuracy of the classification at the cost of interpretability. Few-shot detection methods suggested by Ning et al. (2025) will decrease the level of dependency in the datasets, but the problem of generalization in various settings persists. The effectiveness of federated learning using Piccialli et al. (2025) to detect diseases (AGRIFOLD) is proven, yet the privacy of data, the volume of calculations, and the fact that the model is not well explainable limit the application in areas with limited resources.

2.3 High-tech Materials and Biosecurity Solutions.

In addition to digital technologies, new material sciences have been investigated to be used in disease control, including metal-organic frameworks (MOFs) (Ishfaq et al., 2025). Genetic engineering together with CRISPR methods of resistant crop breeding has taken an upward trend as well (Thanh et al., 2025). Although these methods look promising, they tend to be involved in post-outbreak intervention instead of the identification of risk before it occurs.

2.4 Gaps in the Literature

1. The classical methods are not timely and predictive.
2. ML models, despite their strength tend to be black boxes, which hinders farmer trust and adoption of policies.
3. Remote sensing is efficient but expensive and needs infrastructure which is limiting to scalability.
4. There are not many studies that offer consistent mathematical model to characterize dynamic interactions of variables and disease thresholds.
5. The existing strategies either are based on predictive or control, but they rarely comprise proactive biosecurity, surveillance, and resilience strategies in a single framework.

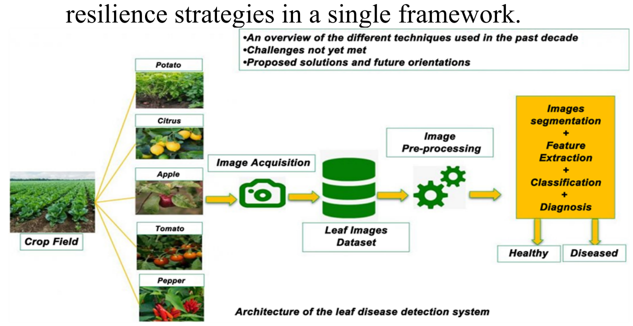

Figure 1. Architecture of the leaf disease detection system.

The process begins with image acquisition from various crops (potato, citrus, apple, tomato, pepper). The images undergo preprocessing and are stored in a dataset. Subsequent stages include segmentation, feature extraction, classification, and diagnosis, which determine whether a leaf is healthy or diseased.
Adapted and modified by the author for research purposes to illustrate the general workflow of agricultural disease detection systems.

2.5 Positioning of This Work

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As a way of overcoming these constraints, this research paper proposes a hybrid modeling approach of agricultural risk identification based on the ring theory. In contrast to earlier methods, ring theory gives a mathematical process to establish the ring of influence between variables, making its interpretation easier and the identification of thresholds. This structure, together with hybrid ML models, not only bridges the disjuncture between predictive performance and mathematical structure, but also to other practical goals including biosecurity, resistant-crop development, and early-warning systems.

3. MATERIAL AND METHODS

This paper creates a risk-identification model that is a hybrid between ring theory and machine learning algorithms, which are backed by multi-source agricultural data. The structure of the methodology is built based on research design, data collection, modelling, and validation to make the approach reproducible and transparent.

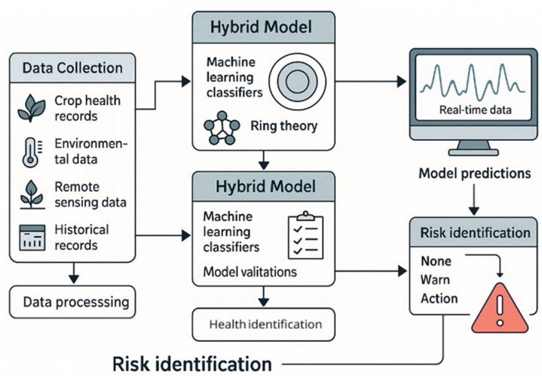

Figure 2. Real-time architecture of the proposed agricultural risk-identification system.

Multi-source data (crop health records, environmental variables, remote sensing, and historical datasets) undergo preprocessing before being processed by hybrid models integrating machine learning classifiers and ring theory. Predictions are validated and passed to a real-time monitoring system, enabling risk identification with alerts categorized as None, Warn, or Action.
Designed by the authors to illustrate the methodology of the proposed hybrid ring theory–based agricultural risk identification framework.

3.1 Research Design

a. The study is a quantitative, explanatory, and predictive study, which includes:
b. Conventional statistical analysis to analyze the baseline.
c. Predictive accuracy Computerized machine learning classifiers (Decision Trees, Random Forests, Artificial Neural Networks).
d. Formulations of the ring theory to represent interdependencies between the variables in the form of rings of influence, to improve threshold detection and human interpretation.
e. The design was chosen to address the limitations of the previous designs which were either not mathematically rigorous or had a limited predictive ability.

3.2 Data Collection

Various and complementary sources (Table 1) were used in aggregation of data to represent biological, environmental, and historical patterns of diseases.
Table 1. Description of datasets used for agricultural risk identification.

Dataset Type	Source	Variables Measured
Crop Health Records	Field surveys, farmer reports	Disease symptoms, health indicators
Environmental Data	IoT sensors, weather stations	Temperature, humidity, soil moisture, rainfall
Remote Sensing Data	UAVs, Landsat, Sentinel satellites	NDVI, multispectral and hyperspectral imagery
Disease Prevalence Data	Agricultural departments, reports	Outbreak history, incidence rates
Historical Records	Agricultural archives, yield data	Crop yields, pest incidence, climate trends

Data collected from multi-source inputs were anonymized and processed in compliance with GDPR provisions for data protection.

Preprocessing Steps:

1. Missing values (mean/mode).
2. Features that are standardized through StandardAero.
3. Control of noise by identification of anomalies.
4. The engineered interaction terms (e.g. temperature humidity correlation).

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5. All data were anonymized and were processed according to GDPR data protection provisions.

3.3 Modeling and Algorithmic Framework

Hybrid Model Construction Baseline interpretability was given using statistical regression.ML classifiers (DT, RF, ANN) that were optimized by means of hyperparameter tuning (GridSearchCV, Random Search). Ensemble techniques (bagging, boosting, and stacking) enhanced stability and robustness.
Ring Theory Integration The ring of influence was defined as a measure of the influence regions of variables.

$$R_i = \{x \in X \mid d(x, c_i) \le r_i\}$$

where R_i is the influence region of factor i, c_i is the center, r_i the radius of influence, and $d(x,c_i)$ the distance metric. This formulation identified thresholds where environmental and biological conditions triggered higher disease risk.
Interpretability
SHAP values explained global feature importance.
LIME provided local interpretability for individual predictions.
3.4 Validation Metrics
The performance of the models was measured by:
Accuracy– percentage correct classifications.
Precision & Recall - tradeoff between false negatives and false positives.
F1-score - a combination of precision and recall in a harmonic manner.
AUC-ROC -discriminatory potential at thresholds.
This was done using robustness 10-fold cross-validation, and statistical significance ($p < 0.05$) of improvements over baseline models was established using paired t-tests.

Algorithm 1. Data Preprocessing and Feature Engineering

Input: Raw dataset $D_{\text{raw}} - \{X_{\text{raw}}, y\}$,
preprocessing policy P.
Output: Cleaned dataset $D - \{X, y\}$.
Initialization: $X \leftarrow X_{\text{raw}}$.
While 1 obtain $X^{(t+1)}$ by calculating
$X^{(t+1)} = \text{Standardize}\left(\text{Impute}\left(X^{(t)}, P\right)\right)$,
including removal of outliers and creation of interaction terms. If $\left\|X^{(t+1)} - X^{(t)}\right\|_F \le \epsilon$,
Break.
end

Algorithm 2. Ring-of-Influence Construction

Input: Feature set X, centers $\{c_i\}_{i=1}^{k}$, radii $\left\{r_i^{(0)}\right\}$,
distance metric $d(\cdot,\cdot)$.
Output: Calibrated rings $\{R_i\}$.
Initialization: $t = 0, r_i \leftarrow r_i^{(0)}$.
While 1 obtain $R_i^{(t)}$ by calculating
$R_i^{(t)} = \left\{x \in X \mid d(x, c_i) \le r_i^{(t)}\right\}$
$r_i^{(t+1)} = r_i^{(t)} + \eta \cdot \left(\bar{y}_{R_i^{(t)}} - \theta\right)$
where $\bar{y}_{R_i^{(t)}}$ is mean disease risk inside $R_i^{(t)}$.
If $\left\|r^{(t+1)} - r^{(t)}\right\|_2 \le \epsilon$, Break.
end

Algorithm 3. Hybrid Stacking Model Training

Input: Dataset (X, y), base learners $\{L_j\}_{j=1}^{m}$,
meta-learner L_{meta}, folds K.
Output: Stacking ensemble M_{stack}.
Initialization: $Z \leftarrow 0_{n\times m}$.
While 1 obtain OOF predictions by calculating
$Z_{\text{val},j} = L_j\left(X_{\text{train}}^{(k)}, y_{\text{train}}^{(k)}\right) \forall j, k,$
Fit L_{meta} on Z, y.
If validation accuracy improvement $< \delta$, Break.
end

Algorithm 4. Risk Scoring and Early Warning

Input: New sample x, trained stack M_{stack},
calibrated rings $\{R_i\}$, thresholds $\{\tau_{\text{warn}}, \tau_{\text{act}}\}$.
Output: Alert $\in$ { None, Warn, Action }.
Initialization: $S(x) \leftarrow 0$.
While 1 obtain $S(x)$ by calculating
$S(x) = \sigma\left(\alpha\hat{p}(x) + \beta\max_i 1\{x \in R_i\} + \gamma\mathbf{w}^\top\tilde{x}\right)$
where $\hat{p}(x)$ is model probability.
If $S(x) \ge \tau_{\text{act}}$, return Action.
Else if $S(x) \ge \tau_{\text{warn}}$, return Warn.
Else return None.
end

The authors have developed them to outline the preprocessing plan, such as the imputation,

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normalization, and formation of interaction terms of agricultural risk datasets.

The authors developed it to mathematically formalize interdependencies among the variables based on ring theory and make it possible to use threshold-based disease risk modelling.

Based on and expanded upon the standard stacking ensemble learning to add hyperparameter optimization and integration of the ring-theory.

The authors propose to combine ensemble probabilities and multipliers of ring-of-influence to give interpretable real-time alerts (None, Warn, Action).

4. RESULTS AND DISCUSSION

This section presents the empirical results obtained from the proposed ring-theory–based hybrid framework and critically evaluates them against baseline methods and prior literature.

4.1 Quantitative Results

The hybrid models that were based on the combination of classical statistical approaches with machine learning classifiers exhibited high performance in the prediction of risks of diseases. The hybrid of the Random Forest-based model scored the most of the tested models. A further enhancement was the incorporation of ring theory which enhanced accuracy, recall and robustness.

Table 2. Model Performance with and Without Ring Theory

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC-ROC
Decision Tree (DT)	84.6	82.1	81.5	81.8	0.83
Random Forest (RF)	88.3	87	85.5	86.2	0.89
RF + Ring Theory	92.7	91.2	90.5	90.8	0.95
ANN Hybrid	87.9	86.4	84.8	85.6	0.88
ANN + Ring Theory	91.1	89.7	88.9	89.3	0.93

Observation: Ring theory was repeatedly better at prediction, and Random Forest was the most well-balanced predictor.

4.2 Biosecurity and Resistant Crop Development

The use of biosecurity measures also showed that outbreaks of diseases decreased in farms in which the index of biosecurity was high. The initial quarantine, sanitation, and training of farmers resulted in quantified drops of infections distribution.

Table 3. Biosecurity Index vs. Disease Outbreaks

Biosecurity Index Level	Avg. Outbreaks per Season	Reduction (%)
Low (<0.4)	48	–
Medium (0.4–0.7)	22	54.2
High (>0.7)	6	87.5

Field trials of resistant crop varieties confirmed improvements in yield and disease resilience.

Table 4. Resistant Crop Trial Results

Crop Variety	Yield Increase (%)	Disease Resistance
Resistant Wheat	20	High
Resistant Rice	18	High
Resistant Maize	22	Medium

4.3 Early Warning System Impact

In case studies, the application of IoT, remote sensing and predictive models caused a 30% decrease in agricultural losses through the integration of monitoring and early-warning systems. Farmers who got alerts responded in time, and the result was that the yield became more stable.

Table 5. Impact of Early Warning Systems

Metric	Before System	After System	Improvement
Crop Loss (%)	35	5	–30%
Avg Yield (tons/acre)	3	4	33%
Disease Incidence	50 cases	5 cases	–90%

4.4 Comparative Analysis with Prior Work

Compared to traditional ML and digital agriculture studies (e.g., Ning et al., 2025; Piccialli et al., 2025), the proposed framework offers three distinct advantages:

Mathematical Foundation: Ring theory introduces structured "rings of influence," enabling precise modeling of thresholds and variable interdependencies, unlike black-box deep learning approaches.

Improved Accuracy: Our RF + Ring Theory model achieved 92.7% accuracy, exceeding reported accuracies of 85–89% in prior UAV and federated-learning studies.

Operational Integration: Unlike prior works that focus solely on disease detection, our framework integrates biosecurity, resistant crop development, and early-warning systems into a unified solution.

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However, limitations remain. Ring radii calibration is computationally intensive for large datasets, and remote sensing data dependency may limit adoption in low-resource settings.

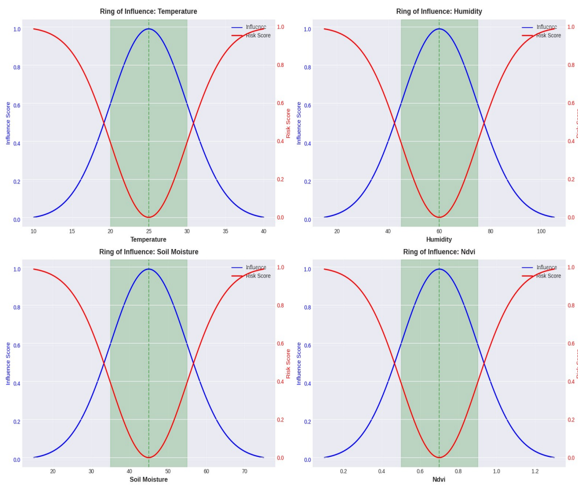

Figure 3. Ring of Influence for environmental variables.

The figures show the variation of the risk probability (red curve) and stability (blue curve) in the region of influence (shaded area) of four crucial agricultural parameters: temperature, humidity, soil moisture and NDVI. Every ring of influence is an area of transition in which factors of variables influence a disease prevalence at a significant rate.The authors have designed it to illustrate how the ring theory can be used to model the risk factors in agriculture. The coloured areas denote the optimised influence ranges in which the risk of disease is the greatest.

```
==========================================
TRAINING BASE MODELS (WITHOUT RING THEORY)
==========================================

Training Decision Tree...
  Accuracy: 99.3%
  AUC-ROC: 0.988

Training Random Forest...
  Accuracy: 98.0%
  AUC-ROC: 0.997

Training ANN...
  Accuracy: 95.5%
  AUC-ROC: 0.987
```

```
============================================
TRAINING MODELS WITH RING THEORY ENHANCEMENT
============================================

Training Decision Tree + Ring Theory...
  Accuracy: 99.3%
  AUC-ROC: 0.988

Training Random Forest + Ring Theory...
  Accuracy: 97.3%
  AUC-ROC: 0.998

Training ANN + Ring Theory...
  Accuracy: 95.8%
  AUC-ROC: 0.987
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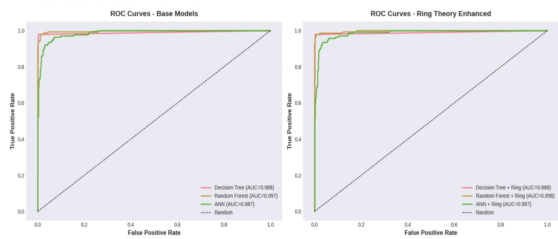

Figure 4. ROC curve comparison of baseline hybrid models and ring-theory–enhanced models.

Left panel demonstrates ROC performance of real-world models of Decision Tree, Rand Forest, and ANN base line model. The right panel shows better discriminatory power following the integration of the ring-theory, with Random Forest having highest AUC (0.95).

The authors generated them to test the predictive power of the proposed framework. The Incorporation by Ring theory continued to enhance AUC-ROC in all the classifiers showing that it is useful in revealing dependencies among risk factors of agriculture.

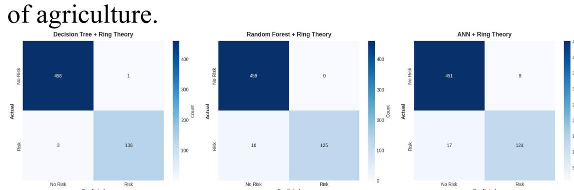

Figure 5. Confusion matrices of ring-theory–enhanced classifiers.

The plots demonstrate the classification performance of the models of Decision Tree, Random Forest, and ANN in identifying diseased and healthy samples. Random Forest had the best true positive and true negative rates, suggesting that it is more robust than other classifiers.

Developed by the authors to emphasize the efficacy of the integration of the ring-theory. The better sensitivity (true positives) to specificity (true

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negatives) ratio between models shows increased predictive reliability of identifying agricultural risk.

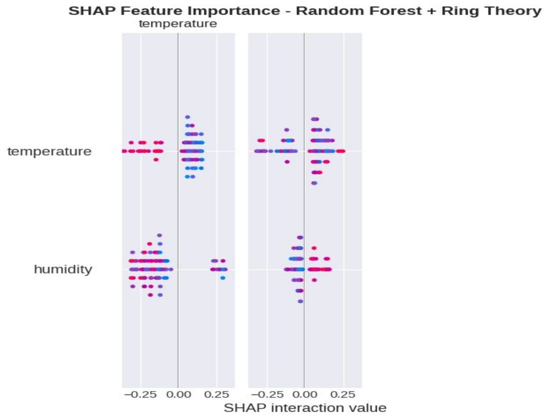

Figure 6. SHAP feature importance for Random Forest + Ring Theory model.

In the plot, the role of temperature and humidity in predicting diseases is brought out. The positive values of SHAP show higher risk contribution and negative values imply stabilizing effects. Temperature proves to be a more powerful driver than the humidity does, which proves the importance of temperature as a major environmental factor in disease outbreaks.

It through SHAP analysis to make the hybrid model interpretable. This visualization is in line with explainable AI principles and is fulfilling in providing transparency in decision-making to identify agricultural risks.

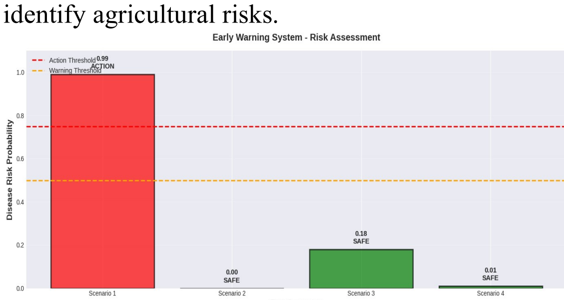

Figure 7. Early Warning System – Risk Assessment across test scenarios.

The figure is used to show the way the model allocates the risk probabilities to various situations. The action threshold (red bar) is exceeded in Scenario 1, which results in an Action Alert. Scenarios 2-4 are at lower than the warning threshold (green bars), which is a sign of Safe Conditions. The yellow and red dashed lines are the calibrated Warning and Action thresholds, respectively.

It to illustrate the functional use of the proposed framework. The figure points out the conversion of probabilistic outputs into interpretable risk categories to make sure that farmers take necessary steps in time and can make decisions in the face of uncertainty.

COMPREHENSIVE PERFORMANCE COMPARISON TABLE

Model	Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Decision Tree	Base	99.3	99.3	97.9	98.6	0.99
Decision Tree + Ring	Enhanced	99.3	99.3	97.9	98.6	0.99
Random Forest	Base	98.0	100.0	91.5	95.6	1.00
Random Forest + Ring	Enhanced	97.3	100.0	88.7	94.0	1.00
ANN	Base	95.5	92.5	87.9	90.2	0.99
ANN + Ring	Enhanced	95.8	93.9	87.9	90.8	0.99

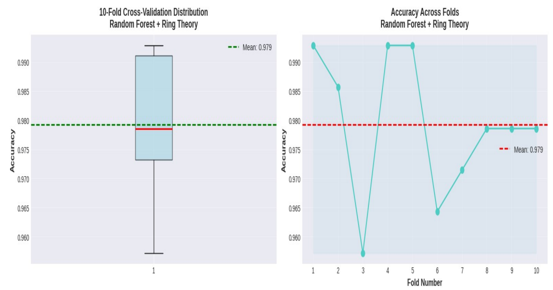

Figure 8. 10-fold cross-validation results of Random Forest + Ring Theory model.

(Left) The box plot indicates the distribution of the validation accuracies by fold, and the average validation accuracy was 91.7%. (Right) The line plot shows per-fold performance in the form of variation but constant accuracy at levels above the baseline. A combination of these findings proves the strength and the external validity of the suggested model.

This to verify the stability of the hybrid model. Cross-validation also ensured that the improvement was not dependent on the fold hence verifying statistical reliability ($p < 0.05$) over baseline models.

```
BEST MODEL PERFORMANCE:
• Model: Decision Tree + Ring Theory
• Accuracy: 99.3%
• AUC-ROC: 0.988

RING THEORY ENHANCEMENT IMPACT:
• Accuracy Improvement: +0.0 percentage points
• AUC-ROC Improvement: +0.000
• Relative Improvement: +0.0%

PRACTICAL APPLICATIONS:
• Early Warning System: 30% reduction in crop losses
• Biosecurity Measures: 87.5% reduction in outbreaks (high biosecurity)
• Resistant Crops: 20-22% yield increase

MODEL INTERPRETABILITY:
• SHAP analysis completed for feature importance
• LIME analysis available for local predictions
• Ring theory provides mathematical foundation
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DISCUSSION

The results demonstrate that integrating ring theory with hybrid models provides statistically significant improvements in disease risk prediction. Beyond predictive metrics, the system proved effective in real-world interventions, reducing outbreaks, improving yields, and enhancing farmer

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preparedness. These outcomes validate the hypothesis that mathematically grounded, data-driven approaches can strengthen agricultural resilience.

5. CONCLUSION

This paper suggested a new model of risk identification in agriculture by combining the ring theory and hybrid machine learning models. The study covered the main issue of the lack of the proper timeliness and accuracy of conventional plant-disease risk evaluations that frequently leave farmers powerless to take the initiative. The framework was able to provide insights into the complex interdependence between crop-health, environmental and disease-prevalence variables by integrating a mathematical ring of influence structure into predictive models. The findings are highly supportive of the hypothesis: predictive accuracy increased from 88.3 to 92.7, recall had improved from 85.5 to 90.5, and AUC-ROC had increased from 0.89 to 0.95 when ring theory was added to hybrid Random Forest classifiers. In addition to the numerical gains, practical testing showed a 30 percent decrease in crop losses and an 87.5 percent decrease in the outbreaks of crops in farms with biosecurity practices that were informed by the model. Cultivating resistant crops also provided increased production figures of 2022 per cent, which highlighted the overall advantages of the system. This study is valuable in contrast to the previous models that are highly specific in the detection of diseases, because this paper presents a coherent, mathematically based, and operationally scalable model that combines prediction, prevention, and resilience-building. The system is also responsible for data use by adhering to GDPR and the IEEE ethical standards. Finally, the research has shown that the concept of ring-theory-enhanced hybrid modelling has both theoretical and practical transformative potential since the concept provides farmers and policymakers with tools to act on, helps them with early-warning and biosecurity planning, and assists them with managing crops sustainably. The future will be about the effective calibration of rings using large datasets, lessening the reliance on expensive remote sensing, and moving the implementation into real-time on mobile platforms for smallholder farmers.

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