



An Interpretable Artificial Intelligence Framework for Poultry Disease Risk Prediction Using Farm Management and Environmental Data

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Abstract – Poultry diseases constrain sustainable agricultural production through mortality, yield loss, and supply chain disruption. While artificial intelligence (AI) can detect risk patterns from routine farm data, practical utility depends on balancing predictive accuracy with model interpretability. This study presents an interpretable AI framework for poultry disease risk stratification. Data from 137 commercial farms (67 positive, 70 negative laboratory outcomes) were processed across 42 variables into four composite indices: Environmental Risk Index (ERI), Farm Biosecurity Risk Score (FBRS), Vaccination Compliance Index (VCI), and Farm Management Risk Index (FMRI), constructed independently of outcome data. Five algorithms (Interpretable Logistic Regression [ILR], Decision Tree, Random Forest, Support Vector Machine [SVM], XGBoost) were evaluated using a leakage-controlled stratified 10-fold cross-validation scheme. SVM achieved the highest classification accuracy (64.29%) and precision (68.75%), whereas ILR achieved the highest discrimination (area under the receiver operating characteristic curve [ROC-AUC] = 0.6508). Multivariable logistic regression revealed that FMRI was significantly associated with higher odds of disease detection (odds ratio [OR] = 2.80, $p = 0.0127$), while FBRS exhibited a protective association (OR = 0.49, $p = 0.0438$), a trend confirmed by SHapley Additive exPlanations [SHAP] attribution. The framework offers a transparent pre-diagnostic tool to guide targeted preventive interventions.

Keywords: Artificial Intelligence; Farm Biosecurity; Interpretable AI; Machine Learning; Poultry Disease.

1. Introduction

Poultry production is essential for global food security and rural livelihoods, yet remains vulnerable to infectious disease outbreaks like fowl cholera and avian influenza (Aroh et al., 2024; Bist et al., 2024; Hambolu et al., 2024; Islam et al., 2024; Mnisi et al., 2024; Ngom et al., 2024a). Disease risk emerges from complex interactions between environmental stressors, biosecurity protocols, vaccination compliance, and routine management practices (Hambolu et al., 2024; Ncho et al., 2025; Ngom et al., 2024a). Biosecurity measures reduce pathogen introduction (Alagesan et al., 2025; Hambolu et al., 2024; Islam et al., 2024; Maduka et al., 2016; Ngom et al., 2024a), whereas environmental stressors impair immunity (Attia et al., 2024; Brugaletta et al., 2022; Ncho et al., 2025; Saeed et al., 2019). In resource-constrained settings, routine questionnaire data provides a cost-effective basis for pre-diagnostic risk assessment.

Deploying machine learning (ML), a branch of artificial intelligence (AI), in agriculture faces resistance due to the "black-box" nature of complex algorithms (Ali et al., 2023; Cartolano et al., 2024; Shams et al., 2024). Explainable AI (XAI) bridges this gap by pairing predictive accuracy with interpretable outputs (Ali et al., 2023; Cartolano et al., 2024; Jagan Mohan et al., 2025; Shams et al., 2024). This study establishes a transparent AI framework for poultry disease risk stratification through:

- Constructing four outcome-independent composite indices from raw farm survey items.
- Evaluating five supervised learning algorithms via leakage-controlled cross-validation.
- Quantifying feature contributions using multivariable odds ratios (OR) and SHapley Additive exPlanations (SHAP) values.

2. Materials and Methods

2.1. Sample and Outcome Definition

A cross-sectional survey of 172 commercial poultry farms recorded 42 variables spanning biosecurity, environment, vaccination, and management. Laboratory testing (bacterial culture/polymerase chain reaction (PCR) for respiratory pathogens) served as the gold standard. After removing 4 records with missing laboratory status and 31 inconclusive cases, N=137 definitive records (67 positive [48.9%], 70 negative [51.1%]) were retained. Laboratory status was strictly isolated from feature engineering to eliminate target leakage.

2.2. Construction of Composite Risk Indices

To address multidimensional collinearity, raw variables were mapped *a priori* into four formative composite indicators (Le et al., 2024; Ngom et al., 2024a, 2024b; Taha et al., 2025). Each index is an unweighted, item-normalized mean score across k_d domain items ($x_{i,j} \in [0, c_j]$) (Taha et al., 2025):

a. Environmental Risk Index (ERI): Quantifies abiotic/environmental stress ($k_E = 4$; higher = greater vulnerability):

$$ERI_i = \frac{1}{k_E} \sum_{j=1}^{k_E} x_{i,j}^{env} \in [0.00, 4.00] \quad (1)$$

b. Farm Biosecurity Risk Score (FBRS): Quantifies physical/procedural barriers ($k_B = 5$; higher = stronger protection):

$$FBRS_i = \frac{1}{k_B} \sum_{j=1}^{k_B} x_{i,j}^{bio} \in [0.00, 4.00] \quad (2)$$

c. Vaccination Compliance Index (VCI): Measures adherence to administration and storage ($k_V = 2$; higher = greater compliance):

$$VCI_i = \frac{1}{k_V} \sum_{j=1}^{k_V} x_{i,j}^{vac} \in [0.00, 2.00] \quad (3)$$

d. Farm Management Risk Index (FMRI): Aggregates operational and sanitation vulnerabilities ($k_M = 4$; higher = greater vulnerability):

$$FMRI_i = \frac{1}{k_M} \sum_{j=1}^{k_M} x_{i,j}^{mgt} \in [0.00, 4.00] \quad (4)$$

To establish the conceptual foundation and measurement standards for the composite predictors, Table 1 details the core specifications, theoretical constructs, item counts, theoretical and observed ranges, and directional interpretations across all evaluated farms (N = 137).

Table 1. Composite Index Specifications (N=137).

Index	Theoretical Construct	Items (k)	Theoretical Range	Observed Range	Direction of Higher Score
ERI	Environmental Adversity & Abiotic Stress	4	0.00-4.00	0.00-3.67	Greater environmental vulnerability
FBRS	Biosecurity Barriers & Protection	5	0.00-4.00	0.00-3.75	Stronger biosecurity protection
VCI	Vaccination Adherence & Cold Chain	2	0.00-2.00	0.00-2.00	Greater vaccination compliance
FMRI	Management & Operational Risk	4	0.00-4.00	0.50-3.25	Greater management vulnerability

2.3. Quality Control, Validation, and Modeling

The missing value (<2.1%) was addressed using k-nearest neighbour (k-NN, k=5) imputation embedded within cross-validation folds. Sensitivity testing confirmed strong rank correlation ($r > 0.94$, $p < .001$) with standardized and weighted index formulations (Le et al., 2024).

To prevent leakage, a Stratified 10-Fold Cross-Validation pipeline was implemented. All preprocessing operations (scaling, k-NN imputation, hyperparameter grid search) were fitted strictly on training folds prior to validating on unseen folds. Five algorithms were evaluated: Interpretable Logistic Regression (ILR, L_2 regularized), Decision Tree (DT, $c_p = 0.01$), Random Forest (RF, 500 trees), Support Vector Machine (SVM, radial basis function [RBF] kernel, $C=1.0$), and eXtreme Gradient Boosting

(XGBoost, $\eta = 0.05$). Global and local interpretations were extracted using SHAP values (Lundberg et al., 2020; Molnar et al., 2020).

3. Results

3.1. Index Distributions and Univariate Analysis

Summary metrics across N=137 farms: ERI (Mean=1.51, standard deviation [SD]=0.70), FBRS (Mean=2.33, SD=0.72), VCI (Mean=1.18, SD=0.69), and FMRI (Mean=2.16, SD=0.49). Univariate χ^2 tests revealed significant disease associations for veterinary visit frequency ($\chi^2 = 14.44, p = .0024$), farm proximity ($\chi^2 = 14.41, p = .0024$), visitor access control ($\chi^2 = 13.25, p = .0013$), and perimeter fencing ($\chi^2 = 12.55, p = .0021$).

3.2. Predictive Performance

The classification models were evaluated across multiple performance metrics to assess predictive accuracy, discrimination (area under the receiver operating characteristic curve, ROC-AUC), and probability calibration (Brier score) under a leakage-controlled cross-validation scheme. Table 2 presents the comparative performance metrics across all five evaluated algorithms.

Table 2. Cross-Validation Model Performance Metrics.

Model	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	ROC-AUC	Brier Score
ILR	59.52	61.11	52.38	66.67	0.6508	0.2412
DT	52.38	51.72	71.43	33.33	0.5317	0.2810
RF	54.76	54.55	57.14	52.38	0.6032	0.2359
SVM	64.29	68.75	52.38	76.19	0.5918	0.2380
XGBoost	45.24	45.45	47.62	42.86	0.5102	0.2915

SVM achieved top classification accuracy (64.29%) and specificity (76.19%). ILR achieved the best discrimination (ROC-AUC = 0.6508), and RF yielded the best calibration (Brier = 0.2359).

3.3. Multivariable Association and Explainability

To evaluate the isolated statistical contributions and directionality of each composite index on disease occurrence while controlling for confounding effects, multivariable logistic regression parameter estimates were computed. Table 3 outlines the model coefficients, standard errors (SE), adjusted odds ratios, 95% confidence intervals (CI), and significance levels.

Table 3. Multivariable Logistic Regression Parameter Estimates.

Predictor	Coefficient (β)	SE	p-value	Adjusted OR	95% CI
FMRI	+1.0296	0.4132	.0127	2.8000	1.2462 – 6.2913
FBRS	-0.7079	0.3511	.0438	0.4927	0.2475 – 0.9806
VCI	-0.3883	0.3198	.2249	0.6782	0.3623 – 1.2695
ERI	+0.2255	0.3168	.4756	1.2529	0.6738 – 2.3300
a.	FMRI: A 1-unit increase in management risk elevated adjusted disease odds by 2.80 times ($p = .0127$).				
b.	FBRS: A 1-unit increase in biosecurity protection reduced disease odds by 50.7% (OR = 0.49, $p = .0438$).				

Global SHAP analysis corroborated these dynamics, ranking FMRI ($| \phi | = 0.3821$) as the top risk factor and FBRS ($| \phi | = 0.2614$) as the principal protective factor (Lundberg et al., 2020; Molnar et al., 2020). At the local level (e.g., Farm #42: FMRI = 2.75, FBRS = 1.25, VCI = 1.00, ERI = 2.25), SHAP attributions ($\phi_{\text{FMRI}} = +0.5210, \phi_{\text{FBRS}} = +0.2110$) shifted the base probability (48.9%) to a high-risk prediction of 65.25%, signaling a need for targeted management intervention (Lundberg et al., 2020).

4. Discussion and Proposed Framework

The findings demonstrate clear trade-offs between complex and interpretable models (Cartolano et al., 2024; Shams et al., 2024; Shwetha et al., 2024). SVM excelled at screening out low-risk farms, while ILR provided full parameter visibility. Tree ensembles suffered performance degradation on this small tabular sample (N=137), highlighting the risk of overfitting (Taha et al., 2025). FMRI (OR=2.80) and FBRS (OR=0.49) confirm the critical role of sanitation, disposal protocols, and physical barriers in mitigating pathogen exposure (Bist et al., 2024; Hambolu et al., 2024; Maduka et al., 2016; Mnisi et al., 2024; Ngom et al., 2024a, 2024b). Associations must be distinguished from direct causation: multivariable odds reflect statistical co-occurrence in cross-sectional data, providing decision-support probabilities rather than clinical proof.

To translate the empirical findings into an actionable workflow for agricultural decision-makers, a structured risk-stratification pipeline was developed. Fig. 1 illustrates the operational architecture of this interpretable AI framework, detailing the sequential progression from raw farm-data intake to human-in-the-loop clinical intervention.

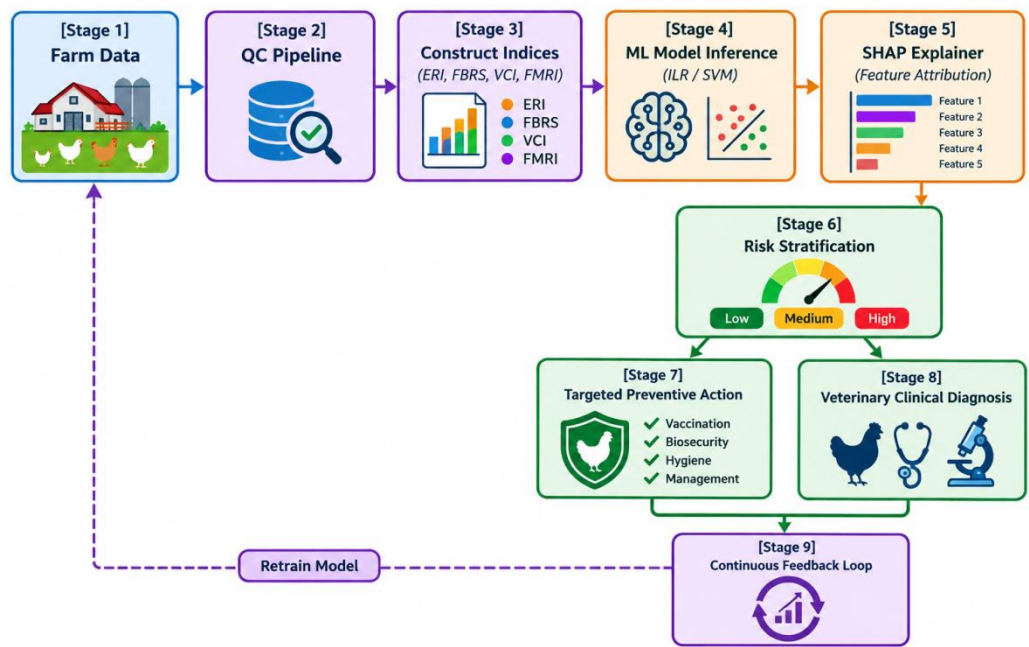


Fig. 1. Operational flow of the interpretable AI framework.

As depicted in Fig. 1, the framework operates as a **human-in-the-loop decision tool** (Cartolano et al., 2024; Neethirajan, 2024; Shams et al., 2024). Model-generated alerts trigger biosecurity audits and prompt veterinary consultation before disease spreads.

5. Conclusion

This study demonstrates an interpretable AI framework for poultry disease risk assessment. SVM provided the highest accuracy (64.29%), while ILR offered optimal discrimination (ROC-AUC = 0.6508) and parameter transparency. Operational management (FMRI) and biosecurity protection (FBRS) were identified as the primary drivers of flock health risk. Future work should validate these indices across larger, multi-regional cohorts and prospective intervention trials (Le et al., 2024; Taha et al., 2025).

References

Alagesan A, Janarthanan G, Balakrishnan A, et al. Training with an evaluation framework: outcomes from a biosecurity training intervention in commercial poultry farms in Tamil Nadu, South India. Vet Med Sci 2025;11(3): e70385.

- Ali S, Abuhmed T, El-Sappagh S, Muhammad K, Alonso JM, Delgado R. Explainable artificial intelligence (XAI): What we know. *Inf Fusion* 2023; 99:101805.
- Aroh IM, Agboje AC, Ogbonna GN, Anyanka SO, Macartan BP, Ohanehi HA, Anigbogu NM. Sustainable poultry farming in developing nations. *Anim Res One Health* 2024;2(3):308–13.
- Attia YA, Hassan RA, Qota EM, Abd El-Hady AM, Bovera F. Climate change effects on poultry industry. *Discov Sustain* 2024; 5:397.
- Bist RB, Bist K, Poudel S, Subedi D, Yang X, Paneru B, Mani S, Wang D, Chai L. Sustainable poultry farming practices: A critical review. *Poultry Sci* 2024;103(12):104295.
- Brugaletta G, Laghi L, Zampiga M, Oliveri C, Sirri F. Heat stress in chickens: Physiology and gut health. *Front Physiol* 2022;13:934381.
- Cartolano A, Fischetti M, Monteriù A, Prist V. Assessing XAI models for smart agriculture. *Multimedia Tools Appl* 2024;83:37225–46.
- Hambolu DA, Olatoye OI, Besong MA, Call DR. Low-cost biosecurity measures and Salmonella in Nigerian poultry. *Sci Rep* 2024;14:20974.
- Islam A, Islam S, Hassan MM, Hossain ME, Debnath NC, Epstein JH, Ahmed MU, Rostal MK. Biosecurity affecting avian influenza in Bangladesh. *One Health* 2024;18:100681.
- Jagan Mohan RNV, Rao PS, Krishna VR, Reddy SR. Integrating AI and XAI for crop predictions. *Front Plant Sci* 2025;15:1451607.
- Le T, Pham QV, Nguyen HD, Tran TV, Hoang AT. Agricultural drought risk assessments: A review. *Nat Hazards Risk* 2024;15(1):2383774.
- Lundberg SM, Erion G, Chen H, DeGrave A, Pruthi JS, Nair B, Bitzan R, Su-In L. Explainable AI for trees. *Nat Mach Intell* 2020;2(1):56–67.
- Maduka CV, Igbokwe IO, Atsanda NN. Appraisal of chicken production and biosecurity in Nigeria. *Scientifica* 2016;2016:1914692.
- Mnisi CM, Mlambo V, Montso PK, Manyeula F, Kumanda C, Moreki JC. Nutraceuticals as components of sustainable poultry production. *Agric Food Secur* 2024;13:24.
- Molnar C, Casalicchio G, Bischl B. Interpretable machine learning—a brief history. In: *Proc. of ECML PKDD 2020 Workshops*, 2020:417–31.
- Ncho CM, Goel A, Kumar S, Choi YH. Abiotic stressors in poultry production: A review. *J Anim Physiol Anim Nutr* 2025;109(1):30–50.
- Neethirajan S. AI and sensor innovations in livestock welfare. *Hum Centric Intell Syst* 2024;4:77–92.
- Ngom RV, Ayissi GJ, Akoussa AMM, Laconi A, Jajere SM, Zangue HA, Mouiche MMM, Awah-Ndukum J, Alamedji RB. Efficacy of biosecurity in disease prevention in livestock in Africa. *Transbound Emerg Dis* 2024;2024:8683715.
- Ngom RV, Laconi A, Mouiche MMM, Ayissi GJ, Akoussa AMM, Jajere SM, Awah-Ndukum J, Alamedji RB. Biosecurity assessment tools in Africa. *Transbound Emerg Dis* 2024;2024:5524022.
- Saeed M, Yatao X, Hassan FU, Arain MA, Abd El-Hack ME, Alagawany M, Dhama K, Chao S. Heat stress management in poultry farms. *J Therm Biol* 2019;84:414–25.
- Shams MY, El-Ghamry A, El-Hefnawy A, Hassanien AE. Enhancing crop recommendations with XAI. *Neural Comput Appl* 2024;36:5695–714.
- Shwetha V, Rao RN, Kumar SP, Prasad KD. Trends in machine learning for poultry health. *J Comput Netw Commun* 2024;2024:8674250.

Appendix A: Item Mapping and Coding Scheme

To facilitate full technical reproducibility and clarify the aggregation process of primary survey data into composite predictors, Table A1 details the complete item-level mapping, domain assignments, response categories, coding criteria, and weighting schemes for all survey variables.

Table A1. Item Mapping and Coding Scheme
(Enables exact reconstruction of indices from raw questionnaire responses).

ID	Item Description	Domain	Categories & Coding	Reverse?	Index	Weight
Q01	Thermal fluctuations	Environment	None (0), Moderate (1), Severe (2)	No	ERI	1.0
Q02	Ventilation system	Environment	Auto (0), Natural (1), Inadequate (2)	No	ERI	1.0
Q03	Humidity control	Environment	Controlled (0), High/Uncontrolled (1)	No	ERI	1.0
Q04	Ammonia odor	Environment	Absent (0), Moderate (1), Strong (2)	No	ERI	1.0
Q05	Perimeter fence	Biosecurity	Complete (2), Partial (1), None (0)	No	FBRS	1.0
Q06	Visitor log / footbath	Biosecurity	Enforced (2), Partial (1), None (0)	No	FBRS	1.0
Q07	Vehicle disinfection	Biosecurity	Functional (2), Absent (0)	No	FBRS	1.0
Q08	Wild bird exclusion	Biosecurity	Sealed mesh (2), Defective (0)	No	FBRS	1.0
Q09	Dedicated footwear	Biosecurity	Mandatory (2), None (0)	No	FBRS	1.0
Q10	Vaccination schedule	Vaccination	Full (2), Partial (1), Non-compliant (0)	No	VCI	1.0
Q11	Cold-chain monitoring	Vaccination	Continuous (2), Intermittent (1), None (0)	No	VCI	1.0
Q12	Litter replacement	Management	Scheduled (0), Delayed (1), Rare (2)	No	FMRI	1.0
Q13	Water treatment	Management	Treated (0), Untreated well (1), Open (2)	No	FMRI	1.0
Q14	Mortality disposal	Management	Incineration/Burial (0), Open dump (2)	No	FMRI	1.0
Q15	Pen equipment sharing	Management	No sharing (0), Shared un-sanitized (2)	No	FMRI	1.0