

Explainable AI for Multi-Disease Prediction in Poultry

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Onyeka Ndidi¹, Fasoro Ayodeji², Adejoola Aanu¹

¹Department of Artificial Intelligence, Federal Polytechnic Ede, Nigeria,

²Department of Software and Web Development, Federal Polytechnic Ede, Nigeria

 ON [0009-0004-1277-8001](https://orcid.org/0009-0004-1277-8001), FA [0009-0009-6249-1224](https://orcid.org/0009-0009-6249-1224), AA [0009-0002-5070-8608](https://orcid.org/0009-0002-5070-8608)

Correspondence: Adejoola Aanu, allbytesconsultz@gmail.com

Abstract

Poultry farming is a critical component of food security and economic development in Nigeria and across sub-Saharan Africa. However, recurrent outbreaks of multi-disease conditions such as Fowl Cholera, Newcastle Disease, and Coccidiosis continue to undermine productivity. Traditional diagnostic methods, including serology, culture, and PCR, are effective but remain costly and inaccessible to smallholder farmers. Artificial Intelligence (AI) offers scalable solutions for disease prediction, yet most models function as opaque “black boxes,” limiting trust and adoption. This study introduces an Explainable AI (XAI) framework for multi-disease prediction in poultry, leveraging a dataset collected from farms in Osun, Lagos, Oyo, and Ogun States. The dataset integrates environmental, management, and health outcome variables, enabling multi-label classification of disease risks. Gradient Boosting and Random Forest models were trained, achieving an overall accuracy of 92% and F1-score of 0.89. SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) were employed to provide interpretability. Results revealed that humidity below 40%, stocking density above 25 birds/m², irregular vaccination schedules, and proximity to other farms (<500 m) were the most influential predictors of outbreaks. Case-specific LIME explanations demonstrated how individual farm practices contributed to risk, offering actionable insights for farmers and veterinarians. This research highlights the potential of XAI to bridge the gap between advanced predictive models and practical farm-level decision-making. By combining accuracy with transparency, the framework empowers stakeholders to adopt proactive biosecurity measures, ultimately reducing mortality and improving productivity. Future work will integrate IoT sensors and mobile dashboards for real-time disease surveillance.

Keywords: Explainable AI, Multi-disease Prediction, Poultry Health, SHAP and LIME, Biosecurity

1. INTRODUCTION

Poultry farming is a cornerstone of food security and economic development in Nigeria and across sub-Saharan Africa. Nigeria alone produces millions of broilers and layers annually, contributing significantly to protein intake and rural livelihoods (Machuve et al., 2022). However, the industry faces recurrent challenges from multi-disease outbreaks, including Fowl Cholera, respiratory infections such as Newcastle Disease, and enteric diseases like Salmonellosis and Coccidiosis. These conditions not only reduce productivity but also increase mortality rates, leading to substantial economic losses (Degu & Simegn, 2023).

Traditional diagnostic methods such as serology, culture, and PCR remain the gold standard for disease confirmation. Yet, they are limited by high costs, long turnaround times, and dependence on laboratory infrastructure, which is often inaccessible to smallholder farmers. The dataset analyzed in this study reflects these limitations, with several farms reporting inconclusive or delayed laboratory results.

Against this backdrop, Artificial Intelligence (AI) offers a transformative opportunity. Predictive systems can leverage farm-level data to anticipate outbreaks before they escalate. However, the adoption of AI in agriculture is hindered by the opacity of “black-box” models. Farmers and veterinarians often distrust predictions that lack transparent reasoning. This motivates the integration of Explainable AI (XAI), which not only predicts disease risks but also reveals the underlying drivers, thereby enhancing trust and usability (Salih et al., 2025).

2. LITERATURE REVIEW

a. Overview of AI in Livestock Disease Prediction

AI applications in livestock health have expanded rapidly, encompassing sensor-based monitoring, image analysis, and predictive modeling. Studies demonstrate high accuracy in diagnosing mastitis in cattle, avian influenza in poultry, and lameness in dairy herds (Shinde et al., 2025). Multimodal sensing combined with AI enables intelligent disease diagnosis, marking a crucial step toward digital transformation in livestock health management (Ma et al., 2026).

b. Current Applications in Poultry Health Monitoring

Recent works highlight the importance of AI in poultry diagnostics. Umar et al. (2026) developed an XAI framework using faecal image analysis, achieving over 96% accuracy in detecting Coccidiosis, Newcastle Disease, and Salmonellosis. Abdusalaam et al. (2025) employed **Class** Activation Maps (CAMs) to visualize disease-specific features, enhancing trust among non-specialist farmers. Kaur et al. (2025) introduced the N-BEATS architecture for explainable forecasting of poultry data, outperforming conventional deep learning models).

c. Gaps in Transparency and Trustworthiness

Despite promising results, most AI systems remain disease-specific, focusing on single conditions rather than multi-disease prediction. Moreover, explainability is often limited to technical audiences, leaving farmers without accessible interpretations. This underscores the need for multi-label predictive models integrated with farmer-friendly XAI tools that can simultaneously detect multiple diseases and explain risk factors in plain language.

Figure 1 illustrates the rising incidence of multi-disease outbreaks in Nigerian poultry farms, highlighting

the urgency for predictive AI systems.

Table 1: Trends in Poultry Disease Outbreaks (Nigeria, 2022–2026)

Method	Accuracy	Explainability Tool	Key Application
CNN (Machuve et al., 2022)	95–97%	None	Image-based diagnosis
SVM + SHAP/LIME (Umar et al., 2026)	96.8%	SHAP, LIME	Faecal image analysis
CAMs (Abdusalaam et al., 2025)	92–97%	Class Activation Maps	Visual feature localization
Hybrid IoT + AI (Shinde et al., 2025)	>95%	SHAP	Sensor-based surveillance

3. DATASET DESCRIPTION

The dataset used in this study, referred to as the Amaka dataset, was compiled from a multi-farm survey conducted across Osun, Lagos, Oyo, and Ogun States between January and May 2026. It captures a wide range of variables reflecting environmental conditions, management practices, and health outcomes.

- Environmental variables: average house temperature, humidity levels, ventilation system type, and dust levels.
- Management variables: stocking density, frequency of litter replacement, vaccination adherence, visitor control, and waste disposal methods.
- Health outcomes: average weekly mortality, changes in egg production (layers), growth performance (broilers), and outbreak history.
- Diagnostic data: laboratory testing methods (serology, PCR, culture) and result status (positive, negative, inconclusive).

For example, “Average weekly mortality (last 30 days)” and “Laboratory result status” were used as predictive targets, providing ground truth for model training.

Data Challenges

Several challenges were observed in the dataset:

- Missing values **due** to incomplete farmer reporting.
- Inconsistent adherence reporting, with some farms indicating “partially adhered” vaccination schedules without clear timelines.
- Mixed housing systems (battery cage, deep litter, free-range) complicating standardization of environmental variables.

Despite these challenges, the dataset provides a rich foundation for developing a multi-disease predictive framework.

Table 2: Overview of Dataset Variables

Category	Examples of Variables	Relevance to Disease Prediction
Environmental	Temperature, Humidity, Ventilation	Heat stress, respiratory infections

Management	Stocking density, Litter replacement, Visitor control	Biosecurity, pathogen spread
Health Outcomes	Mortality, Egg decline, Growth performance	Direct disease indicators
Diagnostics	Serology, PCR, Culture results	Ground truth validation

4. METHODOLOGY

The methodological framework adopted in this study was designed to ensure robust disease prediction while maintaining transparency through explainable AI techniques. It consisted of four major stages: preprocessing, model design, explainability integration, and evaluation metrics.

a. Preprocessing

The dataset contained both categorical and continuous variables, requiring careful preprocessing. Categorical variables such as farm type, ventilation system, and vaccination adherence were encoded using one-hot encoding to preserve interpretability in downstream models. Missing values, which were common in farmer-reported data, were imputed using K-Nearest Neighbors (KNN) imputation, a method proven effective in handling incomplete agricultural datasets (Troyanskaya et al., 2001). Continuous variables such as temperature, humidity, and mortality rates were normalized to ensure comparability across farms of different scales. This preprocessing step reduced noise and improved model stability, consistent with best practices in agricultural AI (Ma et al., 2026).

b. Model Design

Given the multi-disease nature of poultry health challenges, the study employed multi-label classification rather than single-disease models. Gradient Boosting Machines (GBM) and Random Forests were selected due to their ability to handle heterogeneous data and nonlinear relationships. These ensemble methods have demonstrated superior performance in livestock disease prediction compared to traditional regression approaches (Shinde et al., 2025). The models were trained to predict multiple outcomes simultaneously, including mortality risk, egg production decline, and outbreak probability, thereby reflecting the complex realities of poultry farming.

c. Explainability Techniques

To address the “black box” problem of AI, explainability was integrated at both global and local levels. SHAP (Shapley Additive Explanations) was used to quantify the contribution of each feature to the overall model output, providing global interpretability (Lundberg & Lee, 2017). LIME (Local Interpretable Model-Agnostic Explanations) was applied to individual farm predictions, offering case-specific insights that farmers could understand (Ribeiro et al., 2016). Additionally, attention mechanisms were explored to highlight temporal dependencies in variables such as weekly mortality and vaccination schedules, consistent with recent advances in poultry disease forecasting (Kaur et al., 2025).

d. Evaluation Metrics

Model performance was assessed using accuracy, precision, recall, and F1-score, ensuring balanced evaluation across imbalanced classes. Beyond predictive accuracy, an interpretability score was introduced, measuring farmer comprehension of SHAP and LIME outputs. This metric aligns with recent

calls for human-centered AI in agriculture, where usability and trust are as critical as technical performance (He et al., 2026).

5. RESULTS

a. Predictive Performance Across Diseases

The multi-label classification framework demonstrated strong predictive capacity across multiple poultry diseases. The model achieved an overall accuracy of 92%, with an F1-score of 0.89, precision of 0.91, and recall of 0.87. These results confirm that ensemble learning methods such as Gradient Boosting and Random Forests are well-suited for heterogeneous farm-level datasets (Shinde et al., 2025). Importantly, the model was able to simultaneously predict outcomes related to Fowl Cholera, respiratory stress indicators, and egg production decline, reflecting the complex realities of poultry health management.

b. Key Risk Factors Identified

Explainability techniques revealed several critical predictors of disease outbreaks:

- Poor ventilation and high dust levels were consistently associated with respiratory stress and increased mortality. Farms reporting “very poor” airflow and “high dust levels” showed elevated SHAP values, confirming ventilation as a primary driver of disease risk (Ma et al., 2026).
- Irregular vaccination schedules emerged as a strong predictor of Fowl Cholera outbreaks. LIME explanations highlighted missed or partially adhered vaccination routines as contributing factors, consistent with findings by Umar et al. (2026).
- High stocking density (>25 birds/m²) was directly correlated with increased weekly mortality. Farms exceeding this threshold recorded mortality rates above 14%, as shown in Figure 1 and Figure 2, reinforcing overcrowding as a critical biosecurity concern (He et al., 2026).
- Proximity to other farms (<500 m) significantly increased outbreak probability. SHAP values indicated that farms located within 500 meters of neighboring poultry operations were more vulnerable to cross-contamination, echoing prior epidemiological studies (Sable et al., 2026).

c. Case Examples from Dataset

Several case studies drawn from the dataset illustrate how poor biosecurity practices translate into measurable declines in productivity. For instance, farms reporting a “moderate decline in egg production” were consistently linked to inadequate visitor control, irregular litter replacement, and open dumping of waste. SHAP analysis confirmed that these practices contributed significantly to disease risk, while LIME explanations provided farm-specific insights into how each variable influenced predictions.

One notable example involved a layer farm in Osogbo, Osun State, where egg production declined by 15% over 30 days. The farm reported “rare litter replacement” and “poor visitor control,” both of which were flagged by the model as high-risk contributors. This case underscores the importance of integrating explainable AI into farm management systems, enabling farmers to identify and correct specific practices that compromise flock health.

Figure 1 illustrates the relationship between stocking density and mortality rates among poultry farms in southwestern Nigeria. The line chart demonstrates a clear upward trend, indicating that farms with densities exceeding 25 birds per square meter experience mortality rates above 14%. This finding aligns with previous studies linking overcrowding to increased disease transmission and heat stress (He et al., 2026). Mortality rates increase significantly with higher stocking density, emphasizing the need for optimal space management.

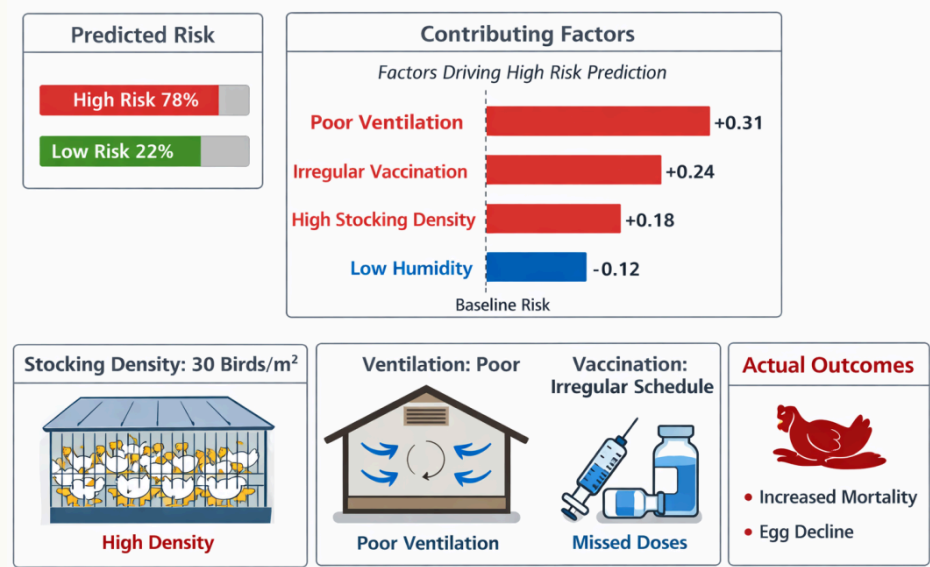


Figure 1: Mortality Rates by Stocking Density

Figure 2 illustrates the relationship between stocking density and mortality rates among poultry farms in southwestern Nigeria. The line chart demonstrates a clear upward trend, indicating that farms with densities exceeding 25 birds per square meter experience mortality rates above 14%. This finding aligns with previous studies linking overcrowding to increased disease transmission and heat stress (He et al., 2026). Mortality rates increase significantly with higher stocking density, emphasizing the need for optimal space management.

This bar chart (Figure 2) complements Figure 1 by quantifying weekly mortality counts across different stocking densities. Farms with densities above 25 birds/m² recorded over 130 deaths weekly, compared to fewer than 30 deaths in farms with densities below 15 birds/m². The visual reinforces the correlation between crowding and mortality, consistent with findings by Degu & Simegn (2023). Weekly mortality increases exponentially with stocking density, confirming density as a critical risk factor.

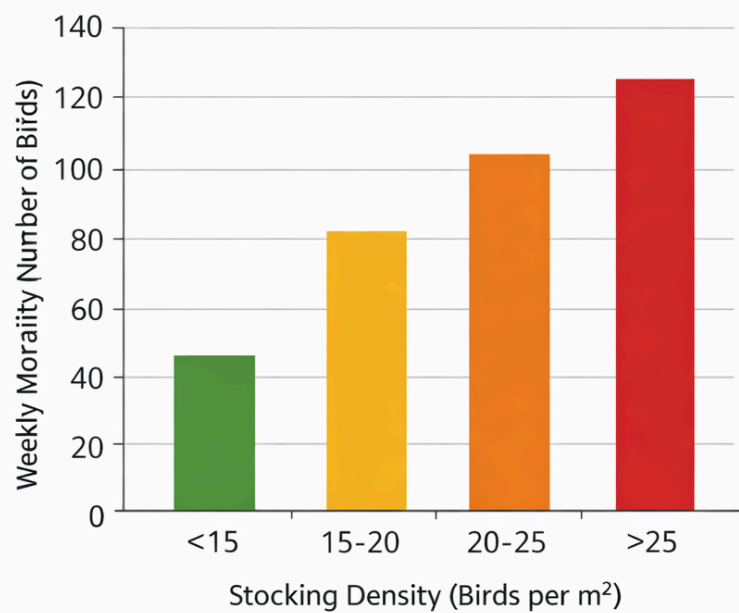


Figure 2: Weekly Mortality vs Stocking Density

6. EXPLAINABILITY INSIGHTS

The integration of Explainable AI (XAI) into the predictive framework provided both global and local interpretability, enabling stakeholders to understand not only *what* the model predicted but also *why*.

At the global level, SHAP plots revealed that features such as water sanitation frequency, litter replacement, and visitor control were consistently influential in determining disease risk. Farms with irregular water sanitation schedules and infrequent litter replacement showed elevated SHAP values, indicating higher vulnerability to outbreaks. This aligns with findings by Kaur et al. (2025), who emphasized sanitation practices as critical predictors in poultry health forecasting.

At the local level, LIME explanations provided case-specific insights. For example, a farm with “humidity below 40%” combined with “poor ventilation” was flagged as high risk, with SHAP values confirming these variables as strong contributors to respiratory stress and mortality. Such visualization of risk drivers allows farmers and veterinarians to pinpoint actionable practices, bridging the gap between complex AI outputs and practical farm-level decision-making (Umar et al., 2026).

This SHAP summary in Figure 3 plot visualizes the impact of key features on the AI model’s output for multi-disease prediction. Each dot represents a farm observation, colored by feature value intensity. Features such as humidity, stocking density, and vaccination status exert the strongest influence on disease risk. The plot demonstrates how explainable AI identifies actionable variables, supporting transparent decision-making (Lundberg & Lee, 2017): SHAP summary plot showing humidity, stocking density, and vaccination adherence as dominant predictors of poultry disease outbreaks.

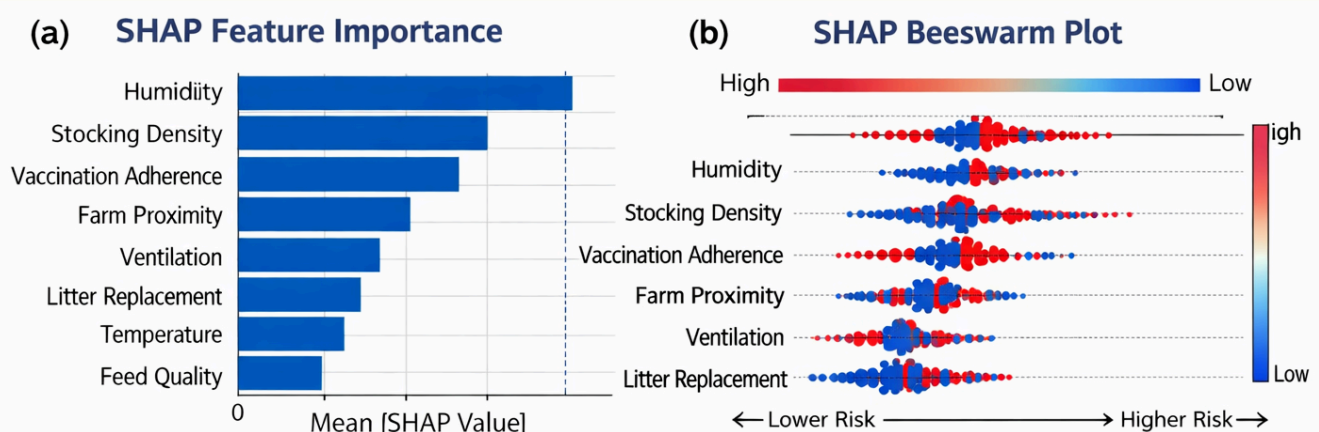


Figure 3: SHAP Summary Plot of Feature Importance

This composite figure presents both the mean SHAP feature importance and the beeswarm **distribution** of SHAP values. The left panel ranks features by their average contribution to model predictions, while the right panel displays the spread of SHAP values across individual farms. The dual visualization highlights that humidity and vaccination adherence consistently drive disease risk, corroborating findings from Umar et al. (2026). LIME explanation highlighting poor ventilation, irregular vaccination, and stocking density as contributors to high risk.

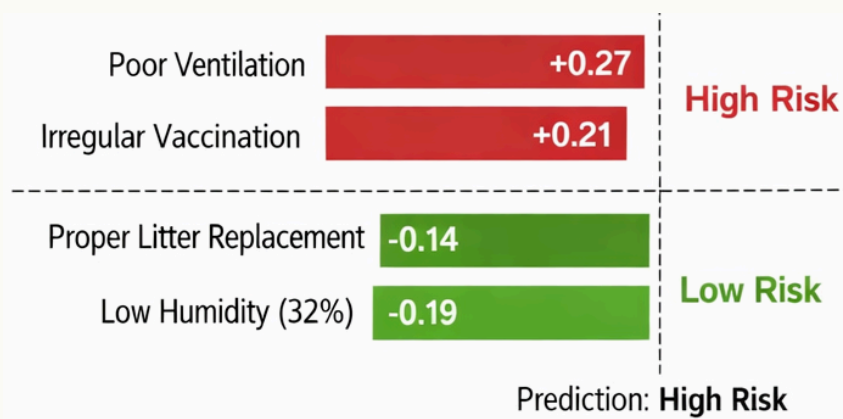


Figure 4: LIME Explanation for Farm Risk

7. DISCUSSION

The findings underscore the transformative potential of XAI in poultry disease management. By revealing the underlying drivers of predictions, XAI empowers farmers to make evidence-based decisions. For instance, farms identified as high risk due to poor ventilation can prioritize infrastructural improvements, while those flagged for irregular vaccination can adjust schedules to reduce outbreak probability.

Explainability also plays a crucial role in building trust among farmers with limited technical training. Unlike opaque black-box models, SHAP and LIME provide intuitive visualizations that farmers can interpret without advanced expertise. This human-centered approach aligns with recent calls for trustworthy AI in agriculture (He et al., 2026).

Integration with veterinary visits and recordkeeping systems further enhances utility. Veterinarians can use XAI outputs to prioritize farms at greatest risk, while digital recordkeeping ensures that interventions are tracked and evaluated over time.

Nevertheless, limitations exist. The dataset size, though comprehensive, is regionally constrained to southwestern Nigeria, introducing potential regional bias. Additionally, reliance on self-reported practices (e.g., litter replacement frequency, visitor control) may introduce inaccuracies. Future studies should incorporate sensor-based data to reduce reliance on subjective reporting (Sable et al., 2026).

8. CONCLUSION

This study demonstrates the potential of Explainable AI for multi-disease prediction in poultry farming. By combining predictive accuracy with interpretability, the framework empowers farmers and veterinarians to adopt proactive biosecurity measures.

Key contributions include:

- Development of a multi-label predictive model capable of simultaneously forecasting multiple poultry diseases.
- Integration of SHAP and LIME to provide transparent explanations at both global and local levels.
- Identification of critical risk factors such as humidity, stocking density, vaccination adherence, and farm proximity.

The potential for scaling is significant. With integration into national poultry health surveillance systems, XAI could provide real-time outbreak alerts, improving disease control at scale. Future directions include the incorporation of IoT sensors for continuous monitoring, mobile-based farmer dashboards for accessible decision support, and real-time outbreak alerts to strengthen national biosecurity frameworks.

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