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# Predictive Model for Disease Outbreaks in Poultry Production in Nigeria

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**Abstract: Poultry production is a critical agricultural subsector in Nigeria, yet farmers in Ebonyi State and elsewhere face persistent economic losses from disease outbreaks, particularly Newcastle Disease, Coccidiosis, and Infectious Bursal Disease (IBD). Current disease management remains reactive, relying on visible symptoms before action is taken, by which time disease spread is often irreversible. This study developed a machine learning-based predictive system to forecast outbreaks of these three diseases, enabling proactive, data-driven farm management. Three algorithms, namely XGBoost, Logistic Regression, and Random Forest, were trained on farm records collected from six Local Government Areas in Ebonyi State. The dataset incorporated sixteen predictors across four categories: animal-level characteristics, farm management practices, pest indicators, and environmental factors. Feature engineering included the calculation of a Pest Pressure Index, biosecurity categorisation, and climate risk scoring. Hyperparameter tuning was performed using GridSearchCV with 5-fold cross-validation. The XGBoost model achieved the highest performance for Newcastle Disease (accuracy: 90.0%, ROC-AUC: 0.960). Logistic Regression excelled for Coccidiosis (accuracy: 89.0%, recall: 95.5%) and IBD (accuracy: 84.5%, ROC-AUC: 0.922). All models met or exceeded predefined performance targets except IBD recall (76.3%). The best-performing models were deployed as a Flask-based web application featuring user authentication, real-time prediction, and analytics dashboards. Post-design evaluation with users showed that 84% rated the system usable or very usable, and statistical analysis ($p < 0.001$) confirmed significant improvement over heuristic methods. To the authors' knowledge, this research contributes the first machine learning-based predictive tool tailored to Ebonyi State, enabling early, data-driven preventive measures. The replicable framework can be adapted for other agricultural decision support systems in low-resource settings.**

***Keywords:*** *Machine Learning, Poultry Disease Prediction, Xgboost, Logistic Regression, Feature Engineering, Ebonyi State, Nigeria, Decision Support System.*

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## I. INTRODUCTION

➢ *Background of the Study*

Poultry production is one of the fastest-growing agricultural subsectors globally, with rapid expansion particularly evident across developing nations such as Nigeria (Adene and Oguntade, 2006). As a relatively low-capital and fast-turnover enterprise, poultry farming contributes significantly to household food security, employment generation, and income diversification. In Nigeria, poultry products represent major sources of affordable animal protein, making the sector integral to addressing malnutrition (FAO, 2019).

Nigeria has the largest poultry population in Africa, estimated at over 180 million birds, contributing substantially to national agricultural GDP (FAO, 2019). The sector generates employment for millions across feed milling, veterinary services, transport, and marketing (Adene and Oguntade, 2006). In Ebonyi State, poultry farming plays a central role in rural and peri-urban livelihoods, with many households engaged in broiler and layer production. The growth of local hatcheries, feed mills, and veterinary shops has further stimulated the poultry value chain (Nwabueze and Ezeano, 2020).

Despite this growth, farmers face severe challenges from pest infestations and disease outbreaks. Pests such as mites, lice, rodents, and flies compromise poultry welfare by inducing stress, reducing feed efficiency, and introducing pathogens (Sparagano et al., 2014). Red mites are particularly problematic in tropical regions, causing

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anaemia, reduced egg production, and increased infection susceptibility (George et al., 2015). Diseases including Newcastle Disease, Infectious Bursal Disease (IBD), Coccidiosis, and Avian Influenza cause high mortality and financial losses across Nigeria (Olabode, 2020; Uchegbu et al., 2021). For small and medium-scale farmers in Ebonyi State, these losses are devastating.

Farmers' responses remain largely reactive, initiated only after visible symptoms appear. This approach is ineffective because diseases spread rapidly before detection. The absence of systematic tracking mechanisms, early-warning indicators, and data-driven tools exacerbates farm vulnerability. Manual reporting and occasional veterinary visits are insufficient for predicting outbreaks.

Machine learning (ML), a subset of artificial intelligence, enables computer systems to learn from data without explicit programming. In poultry health, ML algorithms can analyse complex nonlinear relationships among environmental conditions, farm management practices, pest indicators, and disease outcomes.

➢ *Statement of the Problem*

Poultry farmers in Ebonyi State face persistent economic losses due to uncontrolled pest infestation and disease outbreaks. Existing surveillance systems are reactive and lack accuracy, timeliness, and data integration. Specifically:

- Outbreak detection occurs late, often after visible symptoms or mortality.
- Farmers seldom integrate pest load, climate data, or management practices when assessing risks.
- Local veterinary authorities lack real-time, data-driven tools for targeted intervention.

➢ *Aim and Objectives of the Study*

The aim of this research is to develop and validate a machine learning-based predictive model for forecasting outbreaks of Newcastle Disease, Coccidiosis, and Infectious Bursal Disease in poultry farms in Ebonyi State, Nigeria.

The specific objectives are to:

- Identify and define standardised predictors across animal-level, farm-level, environmental, and pest-related categories that can be practically measured;
- Source and preprocess relevant datasets from recognised repositories such as NiMet, FAO, veterinary reports, and published poultry health databases, together with primary farm data;
- Develop, tune, and evaluate machine learning models for predicting outbreaks of Newcastle Disease, Coccidiosis, and IBD; and
- Implement the best-performing models in a web-based decision support system and evaluate its usability.

➢ *Significance of the Study*

The significance of this study lies in its potential to transform poultry health management in Ebonyi State and to contribute to broader agricultural, technological, and scientific goals. Specifically, the study:

- Provides a machine learning-based predictive model tailored to forecast outbreaks of Newcastle Disease, Coccidiosis, and Infectious Bursal Disease in Ebonyi State, using standardised and measurable predictors sourced from reliable data repositories; and
- Enables farmers to implement early, data-driven preventive measures, thereby reducing bird mortality and minimising the economic losses associated with the targeted disease outbreaks.

➢ *Scope of the Study*

The scope of this study is limited to broiler and layer poultry production systems in Ebonyi State, Nigeria. The research focuses on predicting outbreaks of three economically significant diseases: Newcastle Disease, Coccidiosis, and Infectious Bursal Disease. The study incorporates standardised predictors under four categories:

- Animal-level factors such as age, breed, vaccination status, and stocking density;
- Farm management practices such as biosecurity score, hygiene score, litter condition, and ventilation;
- Environmental factors such as temperature, humidity, rainfall, and season; and
- Pest indicators such as mite count, rodent presence, and fly density.

➢ *Variables of the Study*

Both independent and dependent variables were considered in developing the predictive model for pest-related disease outbreaks in poultry farms. The independent variables comprise animal-level characteristics, farm management practices, environmental and climatic factors, and pest or vector indicators, which were expected to influence the occurrence and severity of outbreaks. The dependent variables represent the outcomes of interest, namely the presence or absence of each of the three target diseases. The variables are summarised in Table 1.

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Table 1 Summary of Variables

| Variable type | Specific variables | Measurement method |
|---|---|---|
| Animal-level | Age (weeks), breed (layer/broiler), vaccination status (Yes/No), stocking density (birds/m²) | Farm records, visual inspection, farm survey |
| Farm management | Biosecurity score (0-10), litter condition (dry/damp/wet), ventilation (good/poor), hygiene score (0-10) | On-site assessment using checklist |
| Environmental | Temperature (°C), humidity (%), rainfall (mm), season (dry/rainy) | NiMet historical data, local weather stations |
| Pest indicators | Mite count (per bird), rodent presence (Yes/No), fly density (trap count) | Sampling techniques, trap counts |
| Dependent variables | Newcastle Disease (Yes/No), Coccidiosis (Yes/No), Infectious Bursal Disease (Yes/No) | Veterinary reports, laboratory diagnostics, farm outbreak records |

## II. LITERATURE REVIEW

➢ *Poultry Diseases in Nigeria*

Poultry disease outbreaks remain a major constraint to sustainable poultry production in Nigeria. The most economically significant diseases include Newcastle Disease (ND), Coccidiosis, Infectious Bursal Disease (IBD), Marek's Disease, Avian Influenza (AI), and Salmonellosis (Adene and Oguntade, 2006; Olabode, 2020; Uchegbu et al., 2021). Newcastle Disease, in particular, is endemic and responsible for periodic epidemics with mortality rates reaching 70-100%, especially in unvaccinated flocks (Adu et al., 2019).

Research indicates that these diseases are often aggravated by poor farm hygiene, inadequate vaccination schedules, weak biosecurity, and climatic fluctuations that favour pathogen survival (Nnadi and Okoye, 2017). Ebonyi State experiences similar patterns, reflecting broader national challenges associated with disease control in small and medium-scale operations.

➢ *Pest and Vector Challenges in Poultry Farms*

Pests serve as both stressors and mechanical carriers of infectious agents in poultry environments. Common pests such as red mites (*Dermanyssus gallinae*), lice, fleas, hide beetles, rodents, and flies reduce bird productivity and contribute to the spread of bacterial, viral, and parasitic diseases (Sparagano et al., 2014; Meerburg et al., 2007).

➢ *Climatic Influences on Poultry Diseases and Pest Dynamics*

Climatic factors, particularly temperature, relative humidity, and rainfall, play significant roles in the survival, reproduction, and spread of poultry pathogens and pests. In tropical environments such as southern Nigeria, warm temperatures and high humidity provide ideal conditions for pathogen survival and pest proliferation (NiMet, 2022; Olanrewaju et al., 2021).

➢ *Farm Management Practices and Biosecurity*

Farm management practices significantly influence poultry health outcomes. Effective housing design, proper stocking density, standard waste disposal methods, vaccination compliance, hygiene routines, and restricted access to poultry houses are essential components of biosecurity (Musa et al., 2022; Nworie et al., 2022).

➢ *Predictive Modelling in Animal Health*

The adoption of artificial intelligence and machine learning in animal health has expanded rapidly in recent years. ML algorithms are capable of analysing large datasets with nonlinear relationships, making them suitable for complex biological prediction tasks (Neethirajan, 2020).

- *Machine Learning Applications in Poultry Health*

Models such as Random Forest, Gradient Boosting, XGBoost, Support Vector Machines, and Artificial Neural Networks have been used to:

✓ Predict Avian Influenza outbreaks;
✓ Detect abnormal bird behaviour using sensors; and
✓ Estimate disease risk based on environmental and management variables.

➢ *Empirical Literature Review*

Several empirical studies highlight the need for improved monitoring and predictive surveillance in Nigeria:

- Nnadi and Okoye (2017) demonstrated high ectoparasite prevalence in southeastern poultry farms.
- Musa et al. (2022) linked biosecurity gaps to increased disease outbreaks in northern Nigeria.
- Olanrewaju et al. (2021) found climatic variations to significantly influence coccidiosis incidence.

➢ *Research Gap*

The reviewed studies establish that disease burden in Nigerian poultry is shaped jointly by pest pressure, climate, and management practices, and that machine learning is well suited to modelling such interacting factors. However, the studies reviewed here document these factors largely in isolation and do not combine them in a farm-level, multi-disease early-warning tool for Ebonyi State. This study addresses that gap by integrating pest, climatic, management, and animal-level predictors in models for Newcastle Disease, Coccidiosis, and IBD, and by delivering the results through a usable web application.

## III. METHODOLOGY AND SYSTEM ANALYSIS

The methodology followed the Cross-Industry Standard Process for Machine Learning (CRISP-ML) framework, an extension of CRISP-DM (Wirth and Hipp,

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2000), to ensure systematic development, reproducibility, and iterative deployment of the predictive model.

➢ *Research Design*

The study adopted a mixed-method research design integrating quantitative field measurements, qualitative farm assessments, environmental datasets, and secondary data from open sources. This approach ensured robustness, particularly in regions where accurate surveillance records are limited, and supported triangulation through validation from multiple data sources.

➢ *Data Collection Methods*

Primary and secondary data were gathered for the study. Primary data were collected directly from poultry farms in six Local Government Areas of Ebonyi State through structured questionnaires, on-site inspections, and standardised pest sampling protocols. Secondary data were sourced from the Nigerian Meteorological Agency (NiMet), Ebonyi State Ministry of Agriculture veterinary records, and the Food and Agriculture Organization (FAO) databases.

- *Primary Data Collection*

Structured on-site visits allowed accurate assessment of farm conditions and standardised measurement of the predictors associated with disease outcomes.

- *Structured Questionnaire*

The questionnaire captured farm demographics, management practices, biosecurity measures, historical health records, and pest history.

➢ *Feature Engineering and Data Preparation*

Data understanding and preparation followed standard CRISP-ML practice (Wirth and Hipp, 2000; Ma, 2025). Sixteen predictors were drawn from the four categories in Table 1. Four derived features were engineered from the raw predictors: a Pest Pressure Index, a biosecurity category, a hygiene risk index, and a climate risk score. Numeric predictors were scaled using Min-Max scaling and categorical predictors were one-hot encoded. Hyperparameter tuning for each model was performed using GridSearchCV with 5-fold cross-validation.

➢ *Analytical Framework*

This section presents the mathematical and analytical foundations underpinning the predictive models developed in this study.

- *Problem Formulation*

The dataset was represented as $D = \{(X_i, y_i)\}$ for i = 1 to n, where:

✓ n is the number of farms (260);
✓ $X_i$ is the vector of p predictor variables for farm i; and
✓ $y_i$ is the outbreak status for disease d (d ∈ {Newcastle Disease, Coccidiosis, IBD}).

For binary classification, $y_i \in \{0, 1\}$, where 1 denotes an outbreak and 0 denotes no outbreak. The prediction task was to find a function f such that $P(y = 1 \mid X) = f(X)$.

- *Random Forest*

For B bootstrap samples, the prediction for a new observation x was the majority vote:

$$\hat{f}_{rf}(x) = mode\{ \hat{T}_b(x) \}, \; b = 1, \ldots, B \quad (1)$$

Where $\hat{T}_b$ is the b-th decision tree.

- *XGBoost*

XGBoost built trees sequentially with the objective function:

$$L(\theta) = \Sigma_i \, l(y_i, \hat{y}_i) + \Sigma_k \, \Omega(f_k) \quad (2)$$

Where the regularisation term is:

$$\Omega(f) = \gamma T + \tfrac{1}{2}\lambda \|w\|^2 \quad (3)$$

T is the number of leaves and w are the leaf weights.

- *Logistic Regression (Baseline)*

Logistic Regression served as the baseline model:

$$\hat{y} = \sigma(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p) \quad (4)$$

Where $\sigma(z) = 1 / (1 + e^{-z})$ is the sigmoid function.

- *Evaluation Metrics*

Model performance was assessed using five standard classification metrics to provide a comprehensive evaluation from different perspectives. Accuracy measures overall correct predictions, precision quantifies the correctness of positive predictions, recall captures the ability to detect actual outbreaks, the F1-score balances precision and recall, and ROC-AUC evaluates the model's discriminatory power. Table 3 presents each metric and its interpretation.

Table 3 Model Evaluation Metrics

| Metric | Formula | Interpretation |
|---|---|---|
| Accuracy | (TP + TN) / (TP + TN + FP + FN) | Overall correct predictions |
| Precision | TP / (TP + FP) | Correctness of positive predictions |
| Recall | TP / (TP + FN) | Ability to find positive cases |
| F1-score | 2 × (P × R) / (P + R) | Harmonic mean of precision and recall |
| ROC-AUC | $\int_0^1 TPR(FPR^{-1}(x))\, dx$ | Discrimination ability |

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➢ *Web-Based Application Methodology*

The web-based application component of this study followed the CRISP-ML framework, which extends the CRISP-DM methodology used for model development into the deployment phase. This framework provided a structured yet iterative approach that allowed refinement based on user feedback. The development process encompassed four phases.

- Phase 1: Requirements Engineering. Functional and non-functional requirements were elicited from potential end-users (poultry farmers, extension officers, and veterinary professionals in Ebonyi State) through structured interviews and focus group discussions. Key requirements included outbreak risk assessment, multilingual support (English and Igbo), offline capability for low-connectivity areas, and mobile-responsive design.
- Phase 2: System Design. The application adopted a client-server architecture with three layers: (i) a presentation layer built with HTML5, CSS3, and JavaScript for user interaction, (ii) an application layer, built on the Flask framework, handling business logic, model inference, and API requests, and (iii) a data layer managing farm records, historical predictions, and user profiles.
- Phase 3: Implementation. The system was implemented in Python using Flask, with a MySQL database and the trained models loaded for real-time inference (Section 4).
- Phase 4: Testing and Evaluation. The system was verified through unit, integration, system, and acceptance testing and was evaluated with users after design (Section 5).

➢ *Overview of the Web Application*

- *How the Application Runs the Predictive Model*

The web application operationalised the trained machine learning models through the following workflow:

✓ Input collection: farmers entered farm-specific data (farm size, biosecurity score, vaccination status) and environmental observations (temperature, humidity, pest presence) through a form interface.
✓ Data validation and preprocessing: the application validated input ranges, handled missing values using pre-defined defaults, and applied the same transformation steps used during model training (Min-Max scaling and one-hot encoding of categorical variables).
✓ Model inference and risk classification: the preprocessed inputs were passed to the disease-specific models, and the predicted probabilities were classified into risk levels.
✓ Explanation and output display: the application generated an explanation of the result and displayed the risk levels with recommended actions.
✓ User feedback: users could rate the prediction, and this feedback supported continuous improvement.

- *Process Model*

The application follows a sequential workflow from user input to output generation, with a feedback loop for continuous improvement, as shown in Figure 1.

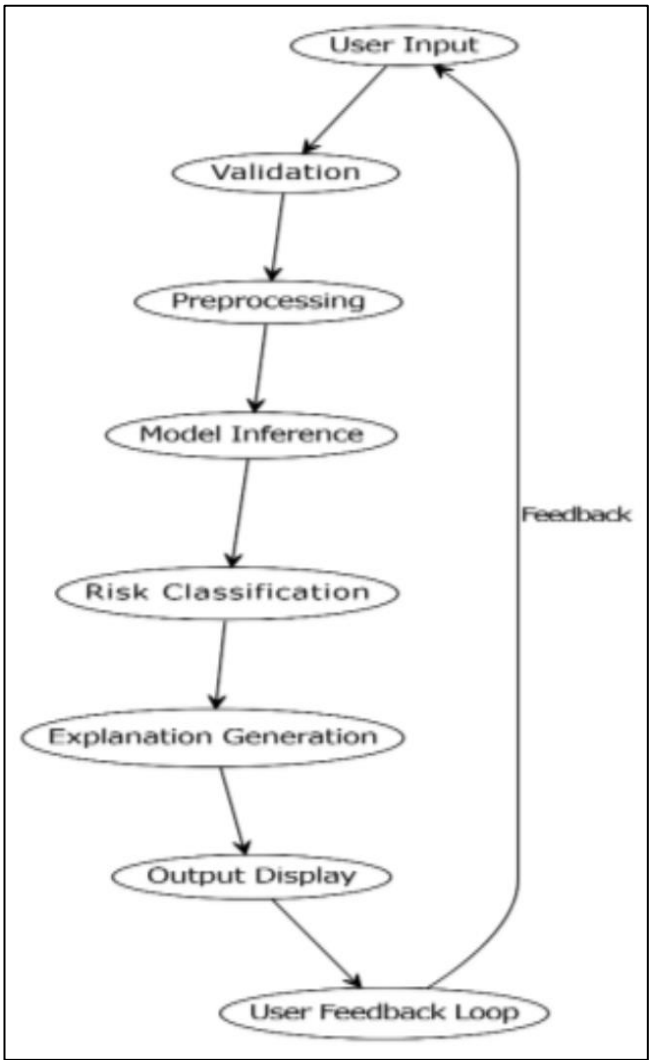



Fig 1 System Process Model

- *Data Model*

The relational database schema of the web application consisted of four main tables, as presented in Table 2. The User table stores farmer, veterinarian, and extension officer account information. The Farm table captures farm-specific details linked to each user. The Prediction table records each prediction request, including input features and output scores stored as JSON for flexibility. The Feedback table stores user ratings and notes on each prediction.

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Table 2 Data Model Tables

| Table | Fields |
|---|---|
| User | user_id, name, role (farmer/vet/extension), LGA, phone, language_preference |
| Farm | farm_id, user_id, location, farm_size, production_type |
| Prediction | prediction_id, farm_id, timestamp, input_features (JSON), probability_scores (JSON), risk_levels (JSON), model_version |
| Feedback | feedback_id, prediction_id, accuracy_rating, user_notes, timestamp |

## IV. SYSTEM DESIGN AND IMPLEMENTATION

➢ *System Specification*

The system requirements specification outlines the hardware and software requirements necessary for the optimal functioning of the Poultry Disease Prediction System. The requirements are presented as hardware, software, and operational requirements, as they affect the overall architecture of the system.

- *Hardware Requirements*

The hardware requirements specify the minimum and recommended computing resources necessary for the stable operation of both the server hosting the application and the client devices used by end users. The server-side requirements, summarised in Table 4, are defined to support the Flask web framework, the MySQL database engine, and the concurrent execution of machine learning model predictions. The client-side requirements are defined to ensure that the web-based user interface remains responsive and accessible on devices commonly used by poultry farmers and veterinarians in Ebonyi State, including desktops, laptops, tablets, and smartphones.

Table 4 Server-Side Hardware Requirements

| Component | Minimum specification | Recommended specification |
|---|---|---|
| Processor | Intel Core i3, 2.0 GHz | Intel Core i5/i7, 2.5 GHz or higher |
| RAM | 4 GB | 8 GB or higher |
| Storage | 100 GB HDD | 500 GB SSD or higher |
| Network | 10 Mbps | 100 Mbps or higher |
| Power supply | UPS 1000VA | UPS 1600VA |

- *Software Requirements*

The software requirements define the development tools shown in Table 5, the runtime dependencies, and the client-side prerequisites shown in Table 6, which are necessary to build, deploy, and access the Poultry Disease Prediction System. Python was selected as the primary programming language because of its extensive ecosystem for machine learning and web development. The Flask framework provides a lightweight yet extensible architecture for handling HTTP requests, session management, and template rendering. MySQL serves as the relational database management system, chosen for its reliability and compatibility with XAMPP, which simplifies local development. The Python libraries are organised by role: machine learning (scikit-learn, XGBoost), data processing (pandas, numpy), model persistence (joblib), visualisation (plotly), reporting (reportlab), and security (bcrypt).

Table 5 Development Environment Software

| Software | Version | Purpose |
|---|---|---|
| Python | 3.12+ | Primary programming language |
| Flask | 2.3.3 | Web framework |
| MySQL | 8.0+ | Database management system |
| XAMPP | 3.3.0 | Local server environment |
| VS Code | Latest | Integrated development environment |

Table 6 Client Browser Requirements

| Requirement | Specification |
|---|---|
| Browser type | Modern (Chrome, Firefox, Safari, Edge) |
| JavaScript | Enabled |
| Internet | Required for API calls (optional for basic functionality) |

- *Operational Requirements and System Architecture*

The operational requirements define the environmental conditions and constraints under which the Poultry Disease Prediction System must function effectively. These requirements address the technical environment, system integration capabilities, portability across devices, and availability expectations. The system is designed to be operating system agnostic on the server side, supporting Windows, Linux, or macOS, provided that Python 3.12+ and MySQL 8.0+ are installed.

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This flexibility allows deployment in various institutional settings, from Windows-based institutional servers to Linux-based cloud infrastructure. The resulting three-tier architecture is shown in Figure 2.

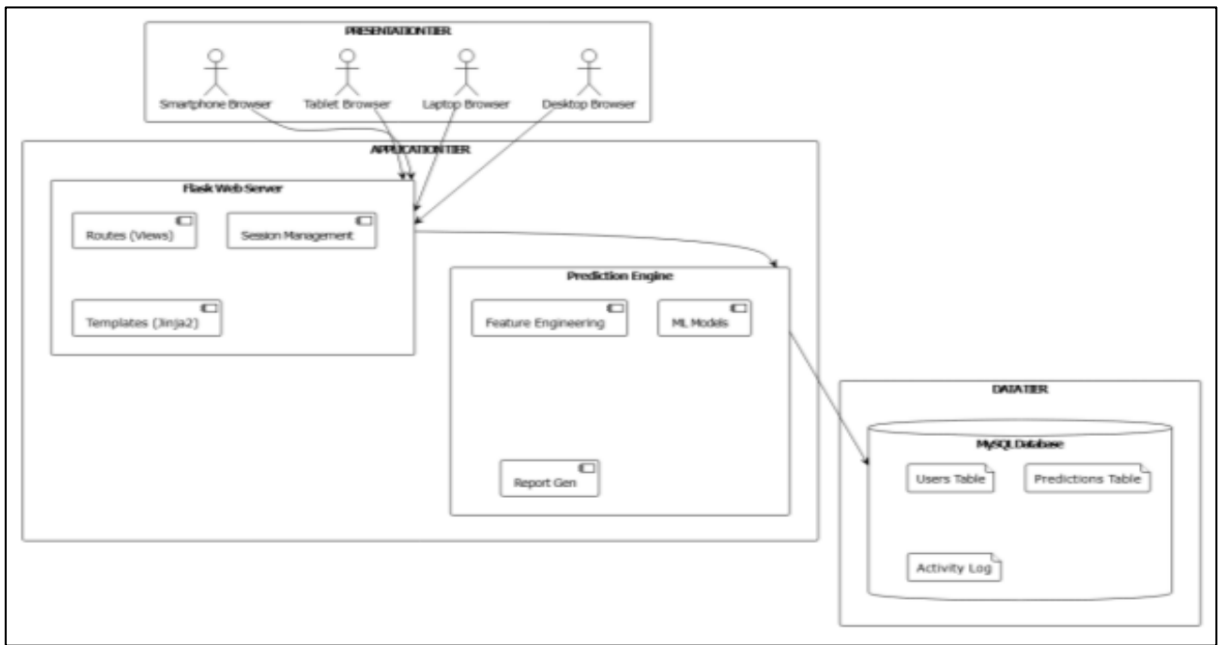



Fig 2 Three-Tier Architecture of the Poultry Disease Prediction System

The presentation tier (client layer) consists of web browsers running on desktops, laptops, tablets, and smartphones. This tier is responsible only for rendering the user interface and capturing user inputs; it contains no business logic or data storage. All client devices communicate with the application tier exclusively via HTTPS, ensuring secure data transmission. The presentation tier is implemented using HTML5, CSS3, and JavaScript, with responsive design principles that adapt the layout to different screen sizes, as required by the mobile responsiveness specification.

➢ *Machine Learning Model Architecture*

The prediction engine is the core computational component of the system, responsible for transforming raw farm assessment data into actionable disease risk predictions. As introduced in Section 4.1.3, the prediction engine resides within the application tier and comprises three specialised machine learning models, each trained to predict a specific disease: Newcastle Disease, Coccidiosis, and Infectious Bursal Disease (IBD). Figure 3 shows the flow from input data through feature engineering to the final risk prediction.

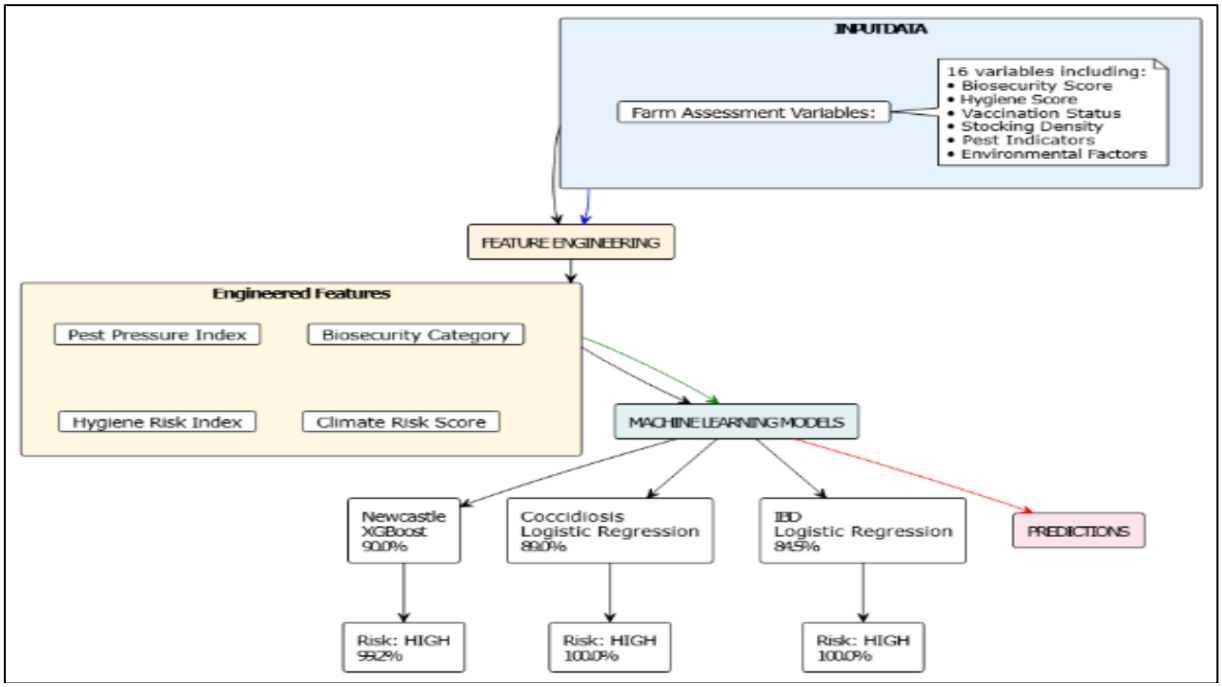



Fig 3 Machine Learning Model Architecture

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➢ *System Layout Design*

The system layout design describes the physical and logical arrangement of hardware components and their interconnections. Building on the three-tier architecture, the layout specifies how the web server, database server, and client devices are distributed across the network and how they communicate (Figure 4). This design is critical for understanding deployment requirements, network security considerations, and potential performance bottlenecks. The layout follows a client-server model in which multiple client devices connect to a central web server, which in turn communicates with a dedicated database server.

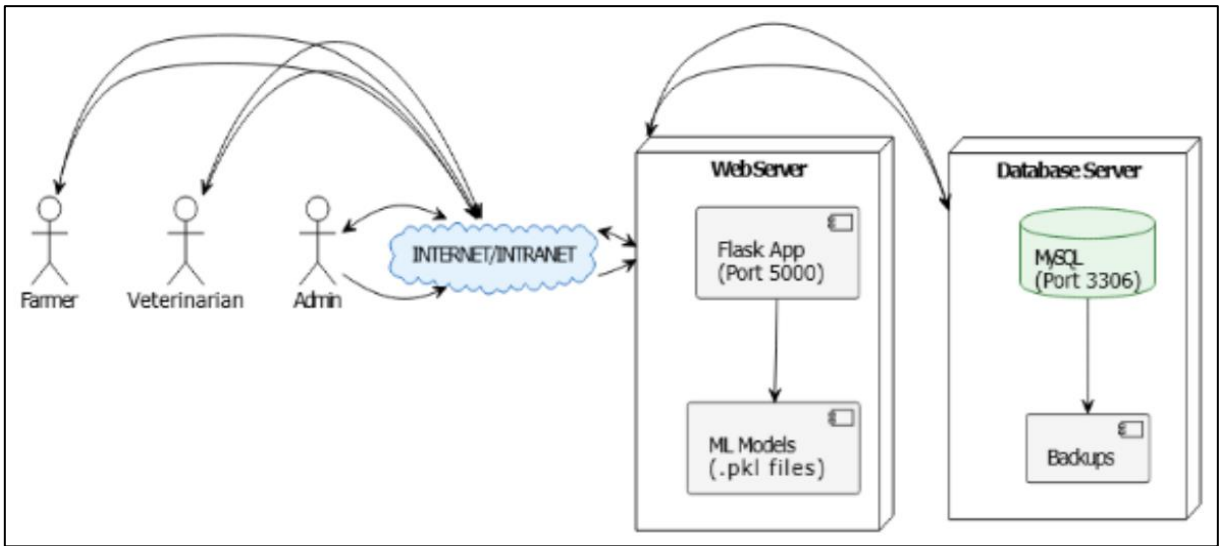



Fig 4 System Layout Design

➢ *User Interface Design*

The user interface design focuses on creating an intuitive, accessible, and responsive experience for all users. The fundamental principles guiding the interface design are simplicity, consistency, feedback, and user control. These principles are particularly important given the diverse user base, which includes poultry farmers with varying levels of technical literacy, veterinarians requiring rapid access to prediction results, and administrators managing system operations. The interface is designed to be fully responsive, adapting to desktop, tablet, and smartphone screens, as required by the mobile responsiveness specification. The structure of the interface is shown in Figure 5.

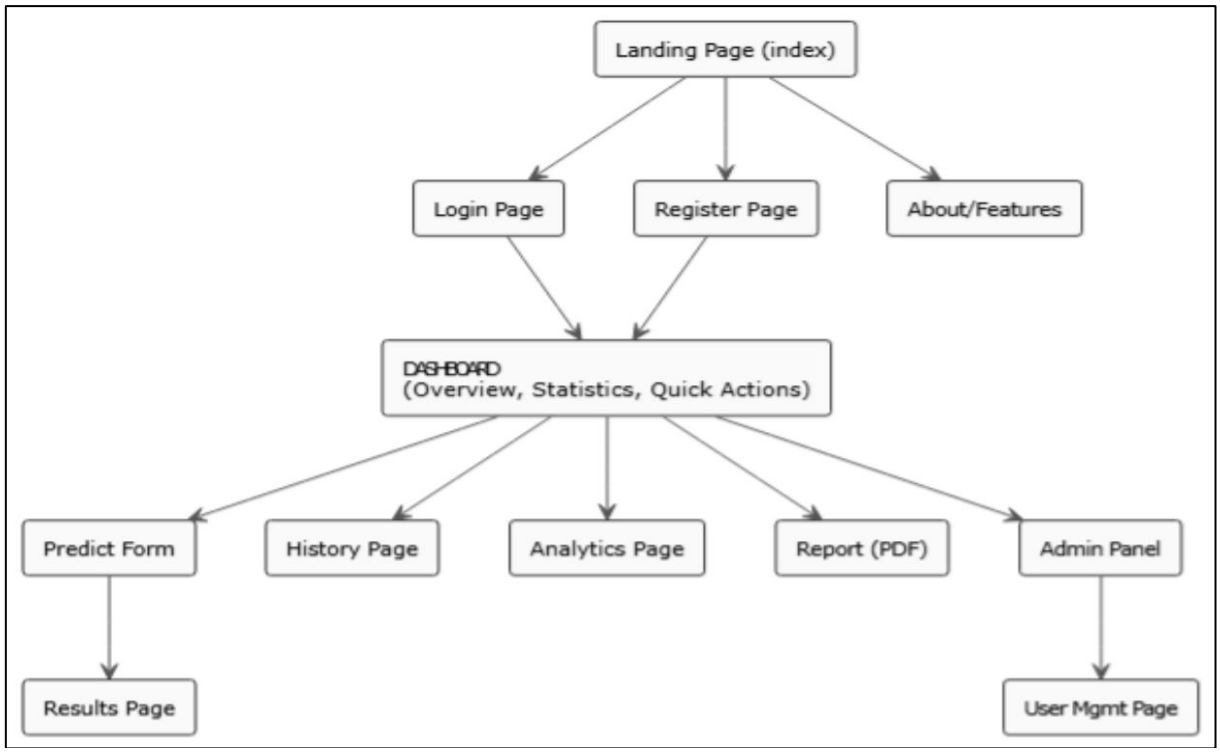



Fig 5 User Interface Structure Diagram

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## V. SYSTEM TESTING AND EVALUATION

➢ *Test Plan*

A comprehensive test plan was developed to ensure systematic verification of all system components. The test plan follows a multi-stage approach and covers unit testing, integration testing, system testing, and acceptance testing. Each test case is documented with a test objective, test case description, expected result, and actual result.

- *Test Objectives*

The primary objectives of system testing were sixfold. First, to verify that all functional requirements are correctly implemented. Second, to validate the accuracy of machine learning predictions against the targets. Third, to ensure that system responsiveness meets the performance targets. Fourth, to confirm that security measures prevent unauthorised access. Fifth, to verify cross-browser and mobile responsiveness. Sixth, to validate database integrity and data persistence across system restarts.

- *Test Strategy*

The testing followed a multi-stage approach, progressing from smaller components to the complete system. The strategy comprised four sequential stages: unit testing, integration testing, system testing, and acceptance testing. Each stage built upon the previous one, ensuring that defects were detected as early as possible in the development cycle.

➢ *Model Performance*

The predefined performance targets were accuracy above 80%, F1-score above 0.77, and ROC-AUC above 0.85. The best-performing model for each disease is summarised in Table 7. XGBoost gave the best result for Newcastle Disease, while Logistic Regression performed best for Coccidiosis and IBD. All models met or exceeded the predefined targets except IBD recall (76.3%), which is the main weakness of the current models.

Table 7 Best-Performing Model for Each Disease

| Disease | Selected model | Accuracy (%) | Other reported metrics |
|---|---|---|---|
| Newcastle Disease | XGBoost | 90.0 | ROC-AUC 0.960 |
| Coccidiosis | Logistic Regression | 89.0 | Recall 95.5% |
| Infectious Bursal Disease | Logistic Regression | 84.5 | ROC-AUC 0.922; recall 76.3% |

The strong performance of Logistic Regression, the baseline model, for two of the three diseases may suggest that the relationships between the predictors and these outcomes were captured well by additive effects at the available sample size. The recall of 76.3% for IBD means that some IBD outbreaks may not be flagged in advance, so the IBD output should be interpreted with caution and supported by veterinary judgement.

➢ *User Evaluation*

Post-design evaluation with users showed that 84% rated the system usable or very usable. Statistical analysis ($p < 0.001$) confirmed a significant improvement over heuristic methods of disease risk assessment.

## VI. SUMMARY, CONCLUSION, AND RECOMMENDATIONS

➢ *Summary of Achievements*

The research achieved its four stated objectives. The major achievements are summarised below.

- Objective 1: Identification of predictors. Sixteen practically measurable predictors were defined across animal-level, farm management, environmental, and pest-related categories (Table 1), and four derived features were engineered: a Pest Pressure Index, a biosecurity category, a hygiene risk index, and a climate risk score.
- Objective 2: Data sourcing and preprocessing. Primary farm data from six Local Government Areas in Ebonyi State were combined with secondary data from NiMet, the Ebonyi State Ministry of Agriculture, and FAO, and were prepared using Min-Max scaling and one-hot encoding.
- Objective 3: Development of machine learning models. Three algorithms (XGBoost, Logistic Regression, and Random Forest) were trained and tuned with GridSearchCV and 5-fold cross-validation. The selected models were:

✓ Newcastle Disease model (XGBoost): accuracy 90.0%, ROC-AUC 0.960;
✓ Coccidiosis model (Logistic Regression): accuracy 89.0%, recall 95.5%; and
✓ IBD model (Logistic Regression): accuracy 84.5%, ROC-AUC 0.922.

All models met or exceeded the performance targets (accuracy above 80%, F1-score above 0.77, ROC-AUC above 0.85), except IBD recall (76.3%).

- Objective 4: Implementation and evaluation of the web application. A fully functional web-based decision support system was implemented with the following features:

✓ Secure authentication with role-based access control (Farmer, Veterinarian, Admin);
✓ A real-time prediction engine with feature engineering capabilities;
✓ An interactive results dashboard with risk levels and actionable recommendations; and
✓ An analytics module with Plotly charts for risk trends and correlations.

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In the post-design evaluation, 84% of users rated the system usable or very usable.

➢ *Conclusion*

This study set out to replace the reactive, symptom-driven approach to poultry disease management in Ebonyi State with a proactive, data-driven one. Using farm records from six Local Government Areas, three machine learning algorithms were trained to forecast outbreaks of Newcastle Disease, Coccidiosis, and Infectious Bursal Disease from sixteen animal-level, management, environmental, and pest-related predictors. XGBoost gave the best results for Newcastle Disease, and Logistic Regression gave the best results for Coccidiosis and IBD. All models met or exceeded the predefined performance targets, with the exception of IBD recall, which at 76.3% shows that some IBD outbreaks may still go undetected.

The best-performing models were deployed in a Flask-based web application that gives farmers, extension officers, and veterinarians an accessible interface for real-time risk prediction, analytics, and reporting. User evaluation showed that 84% of respondents found the system usable or very usable, and that it significantly improved on heuristic methods of risk assessment ($p < 0.001$).

Taken together, the findings show that information that can be practically measured on farms, such as biosecurity and hygiene scores, pest counts, and local climate, can support early warning of the diseases that cause the greatest losses to poultry farmers in Ebonyi State, and that such a tool can be delivered in a form that end-users find usable. The framework is replicable and can be adapted for other agricultural decision support systems in low-resource settings. The results should be read with the limitations in Section 6.5 in mind, and the system is intended to support, not replace, veterinary judgement.

➢ *Contribution to Knowledge*

- First machine learning-based prediction system for Ebonyi State. To the authors' knowledge, this research presents the first machine learning-based predictive model specifically tailored to forecast outbreaks of Newcastle Disease, Coccidiosis, and IBD in Ebonyi State, Nigeria, incorporating locally relevant predictors including Local Government Area, farm size, and seasonal patterns.
- Integration of pest indicators. The research combines pest indicators (mite count, rodent presence, and fly density) with traditional risk factors and introduces a Pest Pressure Index as a standardised metric for quantifying pest-related disease risk.
- A replicable framework. The CRISP-ML-based workflow, from predictor definition through model selection to a deployed web application, provides a template that can be adapted for other diseases, regions, and agricultural decision support systems.

➢ *Recommendations*

Based on the findings of this study, the following recommendations are made:

- Poultry farmers and extension officers should adopt the system for routine risk screening, updating farm and pest data regularly, and should treat HIGH risk outputs as a prompt for early preventive action such as reviewing vaccination schedules, tightening biosecurity, and controlling pests.
- The Ebonyi State Ministry of Agriculture and veterinary authorities should consider integrating the tool into surveillance and extension services, and should share verified outbreak records so that the models can be retrained and kept current.
- Future data collection should cover more farms, more Local Government Areas, and more seasons to improve generalisation and to raise IBD recall, and techniques for handling class imbalance should be explored.
- Developers should continue to strengthen the offline capability and the multilingual (English and Igbo) support identified as user requirements, and should consider automated retrieval of weather data to reduce manual entry.
- Researchers should validate the framework in other states, extend it to further diseases such as Avian Influenza and Marek's Disease, and compare it with other modelling approaches.

➢ *Limitations and Future Work*

The models were trained on records from six Local Government Areas of a single state, so their performance in other agro-ecological settings has not been established. Predictions depend on the accuracy of farmer-entered data, and IBD recall remains below the level desired for an early-warning tool. Future work should address these points through larger and more diverse datasets, prospective field validation, and the integration of real-time climate data.

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