A TEXT-BASED POULTRY HEALTH SYSTEM: AN INTERACTIVE DISEASE DETECTION AND PRESCRIPTION RECOMMENDATIONS

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EXECUTIVE SUMMARY

Poultry farming is vital to Uganda's economy, providing income for many rural households. However, broiler chicken farmers struggle with early disease detection and management, leading to significant flock losses and financial hardship. Although advanced diagnostic tools exist, they are often too expensive and complicated for small-scale farmers in rural areas to access.

This research presents a multilingual, symptom-based poultry disease prediction system, a lightweight, mobile-friendly machine learning solution that addresses the limitations of existing diagnostic tools. By allowing farmers to input observable symptoms like bird behavior, droppings, and flock age through a simple text-based interface, it eliminates the need for costly equipment, lab tests, or other traditional methods.

Several machine learning algorithms were tested to identify the best method for disease prediction, including SVM, Random Forest, XGBoost, and KNN. KNN and SVM performed best, each achieving 96% accuracy and 97% precision, with Random Forest close behind. XGBoost performed poorly, with only 11% accuracy. Although SVM matched KNN in accuracy, it struggled with real-world probability calibration. KNN, on the other hand, provided reliable and interpretable confidence scores, making it the preferred choice for deployment.

The final application is deployed using the Streamlit framework, enabling seamless access across desktop and mobile browsers. It provides real-time disease predictions, along with tailored prescriptions and prevention strategies. Additional features include a QR code for easy sharing, which enhances both the user experience and accessibility. This project bridges the gap between advanced AI and the practical realities of low-resource agricultural settings.

DECLARATION

I Nakimuli Ritah, hereby declare that this is my original work, is not plagiarised and has not been submitted to any other institution for any award.

NAKIMULI RITAH: **Date:** 31/July/2025

APPROVAL

This is to certify that this research titled ”A TEXT-BASED POULTRY HEALTH SYSTEM: AN INTERACTIVE DISEASE DETECTION AND PRESCRIPTION RECOMMENDATIONS” has been done under my supervision and is now ready for submission.

Eng. Ian Raymond Osolo: **Date:** 23/Sept/2025

DEDICATION

This research report is lovingly dedicated to my late mother, whose unwavering belief in me continues to inspire me every step I take and my dear sister Iryn, thank you for your selfless support and for making my education possible.

ACKNOWLEDGMENT

I would like to express my sincere gratitude to all those who have supported me throughout the course of my Master's studies and the development of this thesis. First and foremost, I am profoundly grateful to the Almighty for granting me the strength, resilience, and wisdom to undertake and complete this academic journey. I extend my heartfelt appreciation to my academic supervisor Dr. Ian Osolo and faculty members for their valuable guidance, constructive feedback, and continuous support throughout the research process. I am deeply indebted to my sister, Iryn, for her immense sacrifice and commitment in supporting my education. Her generosity and unwavering support made it possible for me to pursue and complete this degree. To all of you, I extend my deepest thanks and appreciation.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Networks
CDSS	Clinical Decision Support Systems
CRD	Chronic Respiratory Disease
FAO	Food and Agricultural Organization
ICT	Information Communications Technology
IoT	Internet of Things
KNN	K-Nearest Neighbors
MAAIF	Ministry of Agriculture, Animal Industry and Fisheries
ML	Machine Learning
NLP	Natural Language Processing
PII	Personally Identifiable Information
QR	Quick Response
SVM	Support Vector Machine
TAM	Technology Acceptance Model
UBOS	Uganda Bureau of Statistics
UI	User Interface

Chapter 1: INTRODUCTION

1.1 Background

Poultry farming is a vital component of Uganda's agricultural sector, contributing significantly to food security, income generation, and rural development (Poultry Policies , Legislation and Strategies in Uganda Poultry Policies , Legislation and Strategies in Uganda, n.d.). Broiler chickens, in particular, play a central role as a primary source of meat for both local consumption and commercial trade (Byaruhanga *et al.*, 2017). Despite its economic and nutritional importance, poultry farming, especially among smallholders and rural farmers, remains highly vulnerable to disease outbreaks (He *et al.*, 2022), which are a leading cause of production losses and livelihood disruption (Mulondo, 2022).

In recent years, Uganda has seen a steady increase in poultry production, driven by growing consumer demand and commercial investment. Figure 1.1 clearly shows that chicken meat production rose from 44,090 tons in 2000 to more than 53,625 tons in 2002, while hen egg production remained stable at around 20,000 tons (Production & Division, n.d.). This increase reflects the critical role of poultry in meeting the nutritional needs of the country and generating income for farmers.

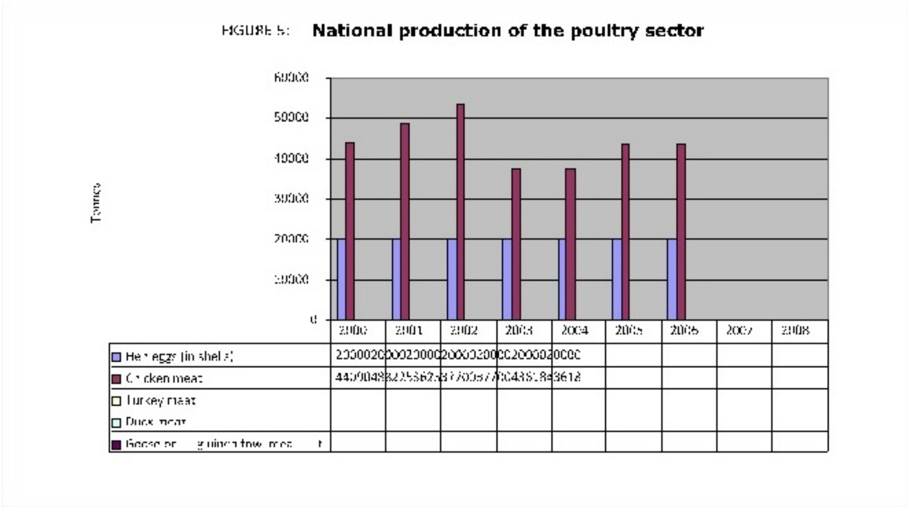

Figure 1.1: National Poultry Production by Type (2000–2008).

Timely and accurate diagnosis of poultry diseases is a cornerstone of effective health management. However, the current landscape of poultry disease detection in Uganda presents several challenges (Mulondo, 2022). Many available diagnostic systems and tools are built for resource-rich environments and rely heavily on sophisticated technologies such as smart cameras (Syazarin *et al.*, 2021), biosensors, thermal imaging (He *et al.*, 2022), or laboratory-based fecal analyses. While these technologies may offer high accuracy (Fahrurrozi *et al.*, 2024), they are financially and logistically inaccessible to the average Ugandan farmer. In addition, systems that focus solely on fecal characteristics may overlook a more holistic view of poultry health, ignoring essential signals such as changes in behavior, feather condition, respiratory distress, feeding habits, and bird age.

In response to these challenges, this study presents the development of a Text-Based Predictive Poultry Health Management System tailored specifically to the Ugandan context. The system leverages machine learning, taking a novel approach that relies on textual symptom input provided directly by the farmer, rather than expensive sensor data. By interpreting visible symptoms, behavioral indicators, dropping descriptions, and bird age, the system aims to deliver real-time disease predictions and corresponding treatment and preventive recommendations.

While the initial model was prototyped using the K-Nearest Neighbors (KNN) algorithm to explore feasibility, further experimentation included evaluation of additional models such as Support Vector Machines (SVM), Random Forest, and XGBoost. Although SVM performed competitively in classification metrics and is known for its robustness in high-dimensional sparse data (Hamilton *et al.*, 2020), real-world testing revealed limitations in its probability calibration and interpretability. As a result, the KNN algorithm was ultimately selected for deployment due to its stable behavior, ease of understanding, and reliable confidence scoring when applied to binary symptom-based input (Suyal & Goyal, 2023).

The final system was implemented using Python's Streamlit framework, chosen for its simplicity, rapid development capabilities, and compatibility with both desktop and mobile web platforms (Kannan *et al.*, 2024). This design enables the application to run seamlessly in a browser, ensuring accessibility even in regions with limited digital infrastructure or device constraints. By removing the need for specialized hardware or complex installation, the system caters directly to the realities of low-resource farming communities.

By combining affordability, multilingual support, and intelligent automation, this system empowers broiler farmers with a practical, easy-to-use tool for managing poultry health. Through a text-based interface, users can input visible symptoms such as droppings type, bird behavior, and flock age to receive real-time disease predictions alongside recommended treatments and preventive measures. The tool contributes to reduced mortality, improved productivity, and more sustainable poultry farming in Uganda.

1.2 Problem Statement

Despite their central role in Uganda's food systems and rural livelihoods, broiler poultry farmers face considerable obstacles in effectively diagnosing and managing flock diseases (Mulondo, 2022). Early-stage disease symptoms are often subtle, varied, and overlapping, requiring prompt identification and action to avoid outbreaks and financial losses. However, small-scale farmers typically lack formal veterinary training and often rely on trial-and-error treatments or delayed veterinary consultations (Salsabil & Syeed, 2023). This results in widespread misdiagnosis, indiscriminate use of antibiotics, and increased mortality rates.

Current disease detection models, where available, are predominantly designed for high-resource settings. They often depend on smart imaging, thermal sensing, or laboratory-grade testing tools that are both cost-prohibitive and logistically impractical for rural Ugandan farmers. Moreover, these models tend to rely on single-modality data inputs, such as fecal texture or temperature anomalies, ignoring a broader symptom spectrum necessary for accurate field diagnosis (Salsabil, 2023). In addition, many of these systems are not localized for Ugandan breeds, environmental conditions, or farming practices, which limits their practical application and adoption. This mismatch between technological capabilities and field realities creates a critical gap, farmers urgently need a solution that is accessible, affordable, and adaptable to their context. Such a system must leverage the full range of observable symptoms, including behavior, appearance, droppings, and age while eliminating reliance on hardware or laboratory diagnostics.

Therefore, this study seeks to bridge that gap through the development of a Text-based, Machine Learning-Driven health management system. The goal is to empower farmers with real-time, data-driven insights that can help them detect diseases early, reduce economic losses, and improve animal welfare using a platform that is truly accessible in Uganda's agricultural context.

1.3 Purpose and Objectives of the Study

Purpose

To design and evaluate a Text-Based Predictive Poultry Health Management System for broiler chickens in Uganda using machine learning. This system should allow users to select the observable symptoms, analyze the input, and deliver disease predictions, prescriptions, and prevention strategies through a mobile-ready application.

Specific Objectives

1. To compile a localized dataset of broiler disease symptoms and conditions (age, behavior, feather condition, droppings).
2. To design and implement an interactive, machine learning-based system using symptom descriptions to predict diseases.
3. To integrate a recommendation engine that provides both treatment and preventive advice based on model outputs.
4. To test and evaluate the application through accuracy metrics and usability on a simple, user-friendly interface suitable for mobile use in rural settings.

1.4 Research Questions

Dataset Compilation: What symptoms and environmental factors are relevant to accurately diagnose broiler diseases?

Model Development: How can machine learning algorithms such as KNN be used to analyze symptom-based input and predict poultry diseases?

Recommendation Integration: What methods can be used to automatically generate treatment and prevention advice based on the predicted disease?

1.5 Significance and Justification of the Study

1.5.1 Justification

Poultry farming in Uganda is both an economic activity and a household survival strategy. Despite its importance, high flock mortality due to poorly managed diseases undermines its potential. Although disease prediction systems exist worldwide, few are financially or logistically viable in Uganda and few are still adapted to local conditions.

This research responds directly to this need by providing a context-aware, cost-effective, and easy-to-use tool that empowers farmers to identify diseases and take timely action without depending on laboratory support or expensive technology. By building the system around farmer-reported symptoms, the solution democratizes access to precision agriculture and aligns with national priorities around food security, agricultural modernization, and rural development.

1.5.2 Significance

Implementing timely disease prediction systems in broiler chicken production offers several key benefits, especially in resource-limited agricultural areas. First, early detection enhances disease control, lowering mortality rates and improving animal health outcomes. This directly boosts productivity, as higher survival rates lead to reduced economic losses and better return on investment. Additionally, accurately identifying diseases helps minimize the unnecessary use of antibiotics, addressing the urgent issue of antimicrobial resistance by reducing improper drug use. Moreover, adopting these technological solutions encourages digital literacy and fosters self-reliance among rural farmers, aiding long-term capacity building. On a broader scale, this project represents an innovative, scalable model that can be tailored to other low-resource agricultural settings, supporting national policy goals and Uganda's broader aims in farm innovation and sustainable development.

1.6 Scope of the Study

1.6.1 Geographical Scope

The study was conducted in Uganda, specifically in the rural and semi-urban areas of Mukono-Lugazi and Luwero-Bombo-Kalule, focusing primarily on broiler farms.

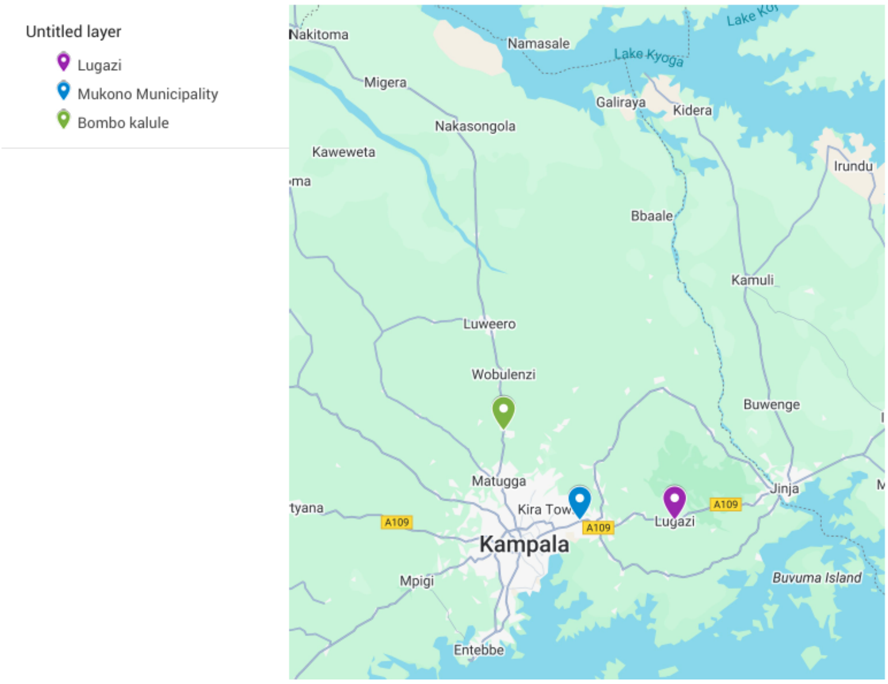

Figure 1.2: Geographical scope.

1.6.2 Poultry Species

The system was primarily designed for Broiler chickens, given their economic significance as a major source of meat. While the core focus remained on broilers, insights applicable to other poultry breeds were also considered during dataset compilation and model development, depending on data availability.

1.6.3 Data Collection

The study compiled a comprehensive dataset on poultry disease symptoms using a combination of literature review, consultations with veterinary experts, and farmer surveys. It emphasized text-based symptom reporting over laboratory or sensor-based diagnostics, aligning with the practical constraints of resource-limited farming environments.

1.6.4 System Development

The project involved the design and implementation of a machine learning-based Predictive Poultry Health System. The system allows farmers to input observed symptoms in text form and receive immediate disease predictions, treatment recommendations, and preventive strategies without the need for expensive diagnostic equipment.

1.6.5 System Evaluation

Preliminary field validation will involve gathering user feedback and testing performance on real-world symptom data. The evaluation will focus on prediction accuracy, relevance of the recommended treatments, and the usability of the interface.

1.6.6 Limitations and Mitigation Strategies

While this study made meaningful progress in predicting broiler disease, certain challenges remain. However, the system was intentionally designed to address these limitations through technical and strategic choices preemptively:

1. Limited Access to Comprehensive Local Data
    - Limitation: Access to fully representative datasets, especially from varied regions and production systems, was constrained, limiting exposure to rare diseases and localized symptom profiles.
    - Mitigation: To address this, the system was trained on a carefully curated dataset combining expert-labeled examples, literature-derived symptoms, and real-farm consultations. Additionally, its symptom-based input structure allows for easy integration of future data without requiring major architectural changes.
2. Constraints on Field-Level Deployment and Scale
    - Limitation: Due to logistical and resource constraints, large-scale real-world testing across farms was not fully conducted
    - Mitigation: The application was designed considering field constraints, supporting offline use, efficient performance on low-end devices, and multilingual input to ensure it remains suitable for a wide range of rural

users once deployed. The system can also be packaged and shared in low-bandwidth environments, ensuring broad usability even before cloud integration.

3. Generalizability beyond Broilers

    - Limitation: The current model is tailored to broiler chickens and may not directly transfer to other poultry types like layers or indigenous breeds.
    - Mitigation: The system architecture and feature design allow straightforward extension. Retraining the model on datasets from other breeds, or adding breed-specific symptom filters, can be performed without major reengineering, generalizing a feasible next step.

4. Interpretability and Trust in Predictions

    - Limitation: Farmers may hesitate to rely solely on AI-generated predictions without understanding how the diagnosis was reached.
    - Mitigation: The app presents confidence scores and ranked disease probabilities, giving users clarity on prediction certainty. Including symptom-based rationale or explanations in future updates would further enhance transparency and trust.

1.7 Conceptual Framework

The conceptual framework for this study outlines the logical and technical foundation upon which the system was developed, demonstrating how symptom-based disease prediction in broiler chickens can be operationalized through machine learning and a user-accessible interface. Rather than focusing on high-cost diagnostic methods, the framework is grounded in symptom observation, algorithmic classification, and human-centered design principles. It integrates components from both data science and rural extension service delivery to support early disease detection in resource-constrained poultry environments.

The key components of the framework include:

1. Farmer Symptom Input

   Farmers act as frontline data collectors, entering observable signs such as behavioral changes, bird age, and characteristics of droppings. This leverages local knowledge and reduces dependency on lab-based diagnostics.

2. Structured Feature Transformation

   Input symptoms are converted into binary-encoded feature vectors that align with the input expectations of machine learning classifiers. This standardization ensures compatibility between human observation and algorithmic inference.

3. Predictive Modeling Layer

   Several classification models were tested, including KNN, SVM, Random Forest, and XGBoost. After empirical comparison, KNN was selected for deployment due to its effective confidence scoring, ease of calibration, and interpretability for non-technical users.

4. Output Layer: Disease Prediction and Prescription

   The system provides real-time feedback by predicting the top likely diseases and suggesting corresponding treatments and prevention guidelines. Outputs are generated in clear language and aligned with common veterinary practices.

5. Interface and Delivery Channel

   A lightweight application, built using Streamlit, ensures that predictions are delivered through a multilingual, offline-capable web interface optimized for mobile and low-end devices.

6. Scalability and Feedback Mechanism (Future Layer)

   While not active in the current version, the architecture anticipates future user feedback loops for improved learning, such as incorporating user confirmation of predictions or new symptom trends from field data.

This framework supports the study's goal of bridging advanced machine learning with the practical needs of small-scale poultry farmers, enhancing accessibility, disease control, and informed decision-making through an integrated, low-cost solution.

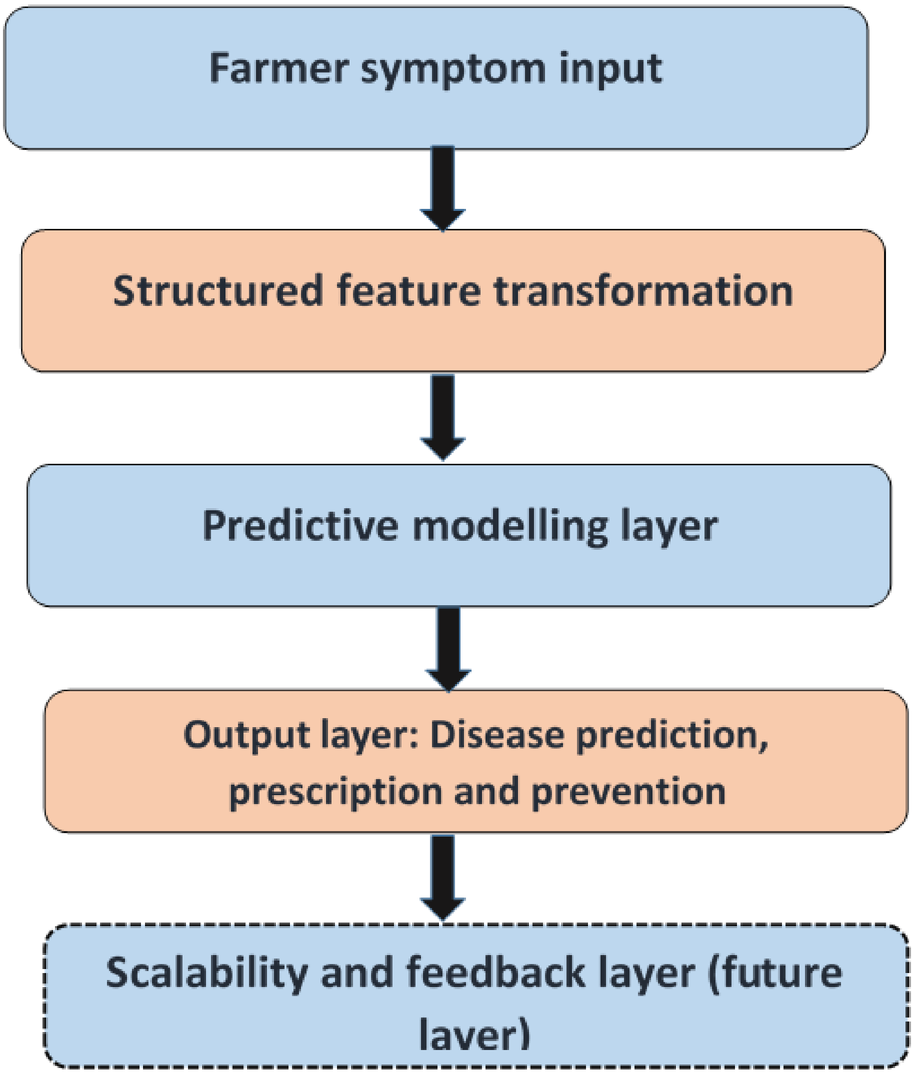

Figure 1.3: Conceptual Framework.

1.8 Chapter Summary

In conclusion, this chapter has presented the foundational context for developing a Text-based predictive poultry health system tailored to the Ugandan broiler farming sector. It has highlighted the critical gaps in existing disease management tools, particularly their inaccessibility to small-scale farmers due to high costs and technological demands. The proposed solution, a mobile-ready machine learning application leveraging symptom-based input seeks to address these challenges by providing an affordable, user-friendly, and context-appropriate tool for early disease detection and response.

Chapter 2: LITERATURE REVIEW

2.1 Introduction

Poultry farming plays a critical role in supporting Uganda's economy, food security, and rural livelihoods. However, effective disease management remains a persistent challenge, particularly for small-scale broiler farmers who often lack access to affordable veterinary services and modern diagnostic tools (Mulondo, 2022). As broiler production continues to grow nationwide, there is increasing demand for innovative, low-cost, and user-friendly solutions for predicting and managing poultry diseases. This chapter presents a review of existing literature on poultry disease management in Uganda, the application of machine learning in agriculture, and the limitations of current detection systems. It also integrates theoretical and empirical perspectives, critically examining the effectiveness of current technologies (Shwetha *et al.*, 2024), identifying knowledge gaps, and setting the foundation for the development of a Predictive Poultry Health Management System tailored to the Ugandan context.

2.2 Poultry Farming and Its Importance in Uganda

Poultry farming constitutes a vital component of Uganda's agricultural sector, providing a significant source of animal protein through meat and eggs (Workers, 2015), while also contributing to household income and employment (Nkukwana, 2023). Recent trends reported by the Uganda Bureau of Statistics (UBOS, 2018) indicate a noticeable shift from indigenous chicken breeds toward exotic broilers driven by increased urban demand and the profitability of broiler production. Markets such as Najjembe and Namawajjolo, along with fast-food outlets like Café Javas and KFC, have further popularized broiler meat consumption across Uganda (Yekosabeth *et al.*, 2022).

Despite the sector's growth, poultry farming faces persistent threats from disease outbreaks, which can wipe out entire flocks, reducing productivity and causing substantial economic losses. For broiler farmers in particular, rapid disease detection and control are critical given the breed's susceptibility to infectious diseases and their short production cycles (Tainika & Duman, 2019).

2.3 Common Poultry Diseases Affecting Broilers

Broiler chickens are susceptible to a range of infectious diseases that can negatively impact flock health, reduce productivity, and lead to significant economic losses (Siddique, 2012). In Uganda, where poultry farming is a key livelihood activity, these diseases present a serious challenge, especially in areas with limited access to veterinary services and diagnostic tools (Nalubwama *et al.*, 2011) The following diseases are among the most prevalent and problematic in Ugandan poultry farming (Byaruhanga *et al.*, 2017, Mulondo, 2022, Shane, n.d.):

- **N**ewcastle disease
  A highly contagious viral disease, Newcastle presents with respiratory distress (coughing, labored breathing, sneezing), green/yellow diarrhea, and nervous signs such as head/neck twisting and paralysis of wings/legs. It often leads to sudden death, loss of appetite, and ruffled feathers. It is also common in birds aged 3–6 weeks (Abdisa & Tagesu, 2017).

- **I**nfectious Bursal Disease (Gumboro)
  Affects birds between 3–6 weeks, targeting the bursa of Fabricius, compromising the immune system. Common signs include white/watery diarrhea, depression, lameness, and paralysis, which increase vulnerability to secondary infections (Teshome *et al.*, 2015).

- **C**occidiosis
  A parasitic intestinal disease common in birds aged 2–8 weeks, characterized by bloody or watery diarrhea, lethargy, weight loss, and depression. It often occurs in intensive systems where hygiene is poor. Though not typically involving respiratory symptoms, its impact on growth and feed efficiency is severe (Grace *et al.*, 2024).

- **A**vian Influenza

  A zoonotic viral disease affecting birds of all ages, marked by respiratory signs (coughing, labored breathing), white/yellow diarrhea, sudden death, and swollen eyes. The system also captures depression, paralysis, and reluctance to move as key symptoms, making it particularly dangerous due to its potential spread to humans and other flocks (Astill *et al.*, 2018).

- **F**owl Cholera

  Caused by Pasteurella multocida, this bacterial disease affects birds of all ages. The system symptoms include green/yellow diarrhea, labored breathing, weight loss, and depression. It can cause high mortality if not managed quickly (Shehata & Hafez, 2024).

  In addition to the above, the system accounts for several other key diseases:

  – Infectious Bronchitis: Causes coughing, sneezing, and eye/nasal discharge, primarily in birds aged 2–4 weeks (Javadov *et al.*, 2020).

  – Marek's Disease: A viral condition noted for paralysis of wings and legs, lameness, and twisting of the neck (Powell, 1986).

  – Infectious Coryza: Presents with swollen eyes, nasal discharge, and sneezing, typically in birds older than 6 weeks (J., 1999).

  – Fowl Pox: Identified by skin lesions, discharge, and ruffled feathers (Station, 1942).

  – Brooder Pneumonia (Aspergillosis): A fungal infection in chicks aged 1–3 weeks with respiratory signs (Saeed & Muhammad, 2014).

  – Salmonellosis: Causes green/yellow diarrhea, lethargy, and weight loss, and is a public health concern (Tariq *et al.*, 2022).

  – Chronic Respiratory Disease (CRD): Characterized by coughing, labored breathing, and eye/nasal discharge, often worsened by poor ventilation (Medical, 1943).

2.4 Importance of Symptom-Based Recognition

The system's detailed inclusion of a wide array of symptoms such as dropping characteristics (like, color and consistency), coughing, lethargy, loss of appetite, and paralysis, plays a critical role in enabling machine learning models to distinguish among poultry diseases that often exhibit overlapping clinical signs. In traditional settings, farmers and veterinary personnel frequently encounter difficulty differentiating between diseases like Newcastle, Avian Influenza, and Chronic Respiratory Disease due to their shared symptoms, particularly respiratory distress and general weakness. However, machine learning algorithms can be trained to recognize subtle patterns and combinations of symptoms that may not be immediately apparent to human observers. This allows for more accurate classification and diagnosis.

By leveraging such granular symptom data, the predictive system becomes a powerful decision-support tool, offering early disease detection, targeted treatment suggestions, and preventive recommendations. This functionality is particularly valuable in resource-constrained rural areas, where access to veterinary laboratories, diagnostic kits, or expert consultation is often limited or absent. Consequently, the system not only empowers farmers to take timely and informed action but also contributes to improved animal welfare, reduced mortality, and greater productivity in the poultry sector.

2.5 Challenges in Traditional Disease Detection

Traditional poultry disease detection methods in Uganda predominantly rely on:

- Farmers' direct observation of visible symptoms (like, changes in behavior, feather quality, droppings)
- Seeking advice from veterinarians, who are often not readily available in rural or under served areas.
- Purchasing over-the-counter medication without laboratory confirmation (Kayendeke *et al.*, 2023).

These methods, while accessible to some extent, present a series of critical limitations:

- Misdiagnosis: Many poultry diseases share common clinical symptoms (such as coughing, lethargy, or diarrhea), making it difficult to distinguish between them accurately. This often leads to incorrect treatments that may worsen the bird's health and increase resistance to drugs.
- Delayed Response: The time taken to contact veterinary professionals or wait for expert intervention can allow diseases to spread rapidly across the flock, leading to significant losses.
- Financial Strain: Professional veterinary services and diagnostic testing are often unaffordable for smallholder farmers, limiting access to accurate diagnosis and effective treatment options.
- Lack of Tailored Interventions: Treatment decisions are often generalized and do not account for specific factors such as bird breed, farm conditions, or age of the flock, reducing treatment efficacy.
- Over-reliance on Single Symptoms: In some interventions, especially those that rely exclusively on analyzing droppings, the risk of misinterpretation is high, as multiple diseases (like, Newcastle, Salmonellosis, and Coccidiosis) can all result in abnormal droppings of similar appearance.
- Inaccessibility of High-Tech Solutions: While some modern poultry farms in developed countries utilize smart technologies such as IoT sensors (Ojo *et al.*, 2022), thermal cameras (Syazarin *et al.*, 2021), and automated health monitoring systems, these are typically cost-prohibitive and technically complex for most Ugandan farmers (Syazarin *et al.*, 2021). Their implementation also requires consistent power supply and internet connectivity, which are often lacking in rural areas (Astill *et al.*, 2018).

These challenges reinforce the urgent need for accessible, cost-effective, and context-aware digital tools that can assist farmers in early disease identification and response.

Systems built on machine learning models that integrate multiple observable symptoms, rather than relying solely on high-tech infrastructure or a single indicator, can bridge this gap and support smarter, faster disease management in Uganda's poultry sector.

2.6 Machine Learning in Poultry Health Management and Theoretical Foundations

From a theoretical perspective, this study draws on principles from the Technology Acceptance Model (TAM) and clinical decision support systems (CDSS) (Holden & Karsh, 2010, Emanuel *et al.*, 2014). These theories emphasize the importance of accessible, easy-to-use technologies that enhance decision-making, particularly in rural farming contexts where digital literacy and infrastructure are limited. In line With these principles, the system developed in this study includes a clear disclaimer: while it provides predictions, prescriptions, and preventive advice, it does not replace the expertise of veterinarians. Users are advised to consult a veterinary professional if symptoms persist or if the system output is uncertain. Additionally, pattern recognition(Abramson et al., 1963) theory underpins the use of machine learning in detecting subtle relationships among overlapping symptoms like coughing, paralysis, and abnormal droppings. By leveraging a text-based, user-driven approach, the system aligns with frameworks for contextual technology design, which prioritize usability in low-resource environments. The application of machine learning (ML) in agriculture, particularly in livestock and poultry health, has demonstrated significant potential (Data, 2023) because ML models are capable of processing large, complex datasets to detect patterns, predict disease outbreaks, and recommend interventions without requiring extensive human interpretation or laboratory diagnostics (Yajie *et al.*, 2023).

In poultry health management, machine learning has been utilized in several ways:

- Image and audio analysis: ML systems analyze bird images or vocalizations to detect abnormalities associated with disease.

- Environmental monitoring: Models use data from sensors tracking temperature, humidity, and air quality to forecast conditions conducive to disease spread.
- Symptom-based prediction: Some systems are trained on datasets containing clinical signs and laboratory results to predict specific illnesses.

Common ML algorithms used in these systems include:

- Decision Trees
- Random Forests
- Support Vector Machines
- Artificial Neural Networks

However, while these innovations offer promising results in controlled environments or commercial farms, many rely on expensive technologies, such as high-resolution cameras, biosensors, or IoT devices that are inaccessible to most smallholder farmers in Uganda due to financial and infrastructural constraints.

Additionally, certain systems focus exclusively on fecal image analysis to diagnose poultry diseases (Machuve *et al.*, 2018). While droppings can offer important health indicators, this single-input method has serious limitations: multiple diseases, including Newcastle, Coccidiosis, Salmonellosis, and Avian Influenza, can cause similar changes in fecal appearance (like, watery, greenish, or bloody droppings). As a result, systems based only on droppings can lead to misclassifications and improper treatment, especially without contextual clinical symptoms.

These gaps highlight the need for a holistic, symptom-based ML system that is affordable, tailored to the local context, and capable of differentiating between diseases with overlapping indicators, thereby offering more accurate and actionable support to poultry farmers in resource-constrained settings.

2.7 Limitations of Existing Models

Despite advancements in poultry disease prediction through machine learning and digital technologies, most existing models present significant limitations that hinder practical application in settings like Uganda.

- Dependence on High-Cost Equipment: Many current models require advanced tools such as sensors, high-resolution cameras, or biosensors to collect physiological or behavioral data. These technologies are cost-prohibitive and infrastructure-dependent, making them unsuitable for smallholder farmers in rural or semi-urban Uganda (He *et al.*, 2022).

- Over-Reliance on Single Data Types: A considerable number of existing systems focus exclusively on one indicator, such as fecal image analysis to detect diseases. However, this is problematic because multiple poultry diseases can produce similar fecal appearances (like, greenish or watery droppings), leading to potential misclassifications and mistreatment.

- Limited Multi-Symptom Integration: Several tools do not incorporate a wide range of clinical signs such as coughing, lethargy, feather condition, or paralysis. This limits diagnostic depth, especially for diseases that share overlapping symptoms, as is common in poultry health.

- Farmer Accessibility and Usability Issues: Even where digital tools exist, many feature complex user interfaces, require stable internet connectivity, or present language barriers. These factors discourage adoption, especially among rural farmers with limited digital literacy.

- Neglect of Text-Based Symptom Input: As noted by (Salsabil, 2023), few systems make use of textual symptom reporting, which can be more accessible and cost-effective. Collecting symptoms via structured forms or chat-bot-style interactions on mobile phones would allow farmers to contribute valuable diagnostic data without the need for technical hardware.

2.8 Opportunities for a Predictive Poultry Health System

Empirical studies like those by Syazarin *et al.* (2021) and Machuve *et al.* (2018) demonstrate high-accuracy poultry disease diagnosis using thermal imaging and fecal analysis. However, these rely on expensive equipment and uninterrupted power, limiting their feasibility in Uganda. Others, such as Salsabil & Syeed (2023), explored machine learning classification using clinical datasets, but often ignored localized symptoms or text-based inputs. In contrast, our study responds to these gaps by using multi-symptom, binary-encoded text data, enabling a more inclusive and accessible tool for rural farmers.

The current gaps create opportunities to innovate by developing a system that:

- Uses symptom descriptions provided by farmers through simple text inputs.
- Applies machine learning algorithms to predict the likely disease.
- Provides treatment prescriptions and preventive advice without expensive infrastructure.
- Is affordable, accessible, and locally relevant for Ugandan farmers.

Such a system would empower farmers with tools to detect diseases early, reduce mortality rates, cut down veterinary costs, and promote sustainable farming practices.

2.9 Summary of Literature Gaps

The literature reveals that poultry farming remains a key pillar of Uganda's food security and economy, yet disease management in broiler chickens remains a persistent challenge. Farmers largely depend on visual symptom observation and ad hoc treatment methods, which often result in misdiagnosis and significant losses. Traditional methods are constrained by delays in veterinary access, reliance on costly laboratory tests, and the unaffordability of high-tech disease detection systems.

A wide range of broiler diseases, including Newcastle, Infectious Bronchitis, Avian Influenza, Coccidiosis, Marek's, Fowl Cholera, and others, present overlapping symptoms such as coughing, diarrhea, lethargy, and sudden death. This symptom overlap makes accurate diagnosis difficult through visual inspection alone, especially for under-resourced farmers.

Many existing digital and AI-driven poultry health models employ high-cost hardware like sensors, cameras, and image-processing tools (especially fecal image analysis). However, such systems are often inaccessible in the Ugandan context due to cost, infrastructure, and regional irrelevance. Moreover, relying solely on fecal characteristics is insufficient, as different diseases may present similar droppings, increasing the risk of misdiagnosis.

Machine Learning (ML) offers a trans-formative alternative. ML algorithms such as Decision Trees, Random Forests, SVMs, and Artificial Neural Networks have been used globally for livestock disease detection. While these models are promising, they often lack adaptability to localized farming conditions and exclude text-based symptom input, an area with strong potential for rural and small-scale applications.

The proposed Predictive Poultry Health System seeks to fill these gaps by enabling symptom-based disease detection through a user-friendly interface. It uniquely integrates a wide array of symptoms, including droppings, coughing, appetite loss, paralysis, and more into a model that can provide reliable disease predictions and treatment suggestions without the need for expensive tools.

This chapter has highlighted the significant limitations of existing models and emphasized the critical need for localized, data-driven, low-cost, and accessible solutions. The proposed system thus aligns with both technological innovation and real-world practicality in Ugandan poultry farming.

Chapter 3: METHODOLOGY

3.1 Overview

This chapter describes the research methods employed in the design, development, and evaluation of a Text-Based Predictive Poultry Health Management System, aimed at supporting broiler farmers in Uganda. The system leverages machine learning, specifically a K-Nearest Neighbors (KNN) classifier to predict poultry diseases based on symptoms provided by the user in text format. It also integrates a prescription recommendation module to guide treatment and prevention strategies.

The methodology covers data collection, preprocessing, model training, system implementation, and evaluation guided by the need to create a low-cost, farmer-friendly, and mobile-ready decision-support tool.

3.2 Research Design

This study uses a mixed-methods research design that combines both qualitative and quantitative approaches to ensure the solution is both practical and technically sound. This approach enables the researcher to gather detailed insights from experts and farmers, while also validating the system using measurable performance data.

The process involved the following stages:

- Problem Identification (Qualitative): Conducted through literature review, consultations with veterinary experts, and farmer surveys to understand challenges in poultry health management and identify relevant symptoms.
- Requirements Analysis (Qualitative → Quantitative): Translated farmer-reported conditions and expert knowledge into structured variables (age, droppings, and symptom features) suitable for dataset compilation.
- System Design and Implementation: Developed a machine learning–based pre-

dictive system (KNN model) trained on the dataset to predict broiler chicken diseases.

- Evaluation: Model performance was assessed using accuracy, precision, and related metrics, with results cross-checked against expert opinions to validate its real-world applicability.

By combining qualitative insights with quantitative analysis, this study ensured that the system is both user-centered and data-driven.

3.3 Study Area

The geographical scope of the study is Uganda, with a focus on broiler farms located in rural and semi-urban regions of Mukono-Lugazi and Luwero-Bombo-Kalule. These areas were selected due to their high poultry density. The context-specific design ensured that the system aligns with local farming practices, disease profiles, and digital access limitations.

3.4 Data Collection

3.4.1 Sources of Data

Data was compiled from multiple primary and secondary sources to ensure contextual relevance and accuracy:

- Literature Review: Scientific journals, veterinary textbooks, and poultry health manuals were reviewed to establish known disease-symptom relationships (He *et al.*, 2022).

- Veterinarian Consultations: Interviews with local poultry health experts validated and refined the list of symptoms for each disease.

- Farmer Surveys: Structured questionnaires were administered to poultry farmers to understand common disease symptoms observed in the field and their typical terminology.

3.4.2 Types of Data Collected

- Disease-Symptom Matrix: A binary mapping of diseases to their characteristic symptoms (like, coughing, lethargy, diarrhea types).
- Droppings and Age Variables: Symptom variants based on droppings appearance and bird age in weeks.

3.4.3 Sources of Symptoms, Treatment Protocols and Prevention Strategies

The list of symptoms used in this study was compiled through a combination of literature review, veterinary consultations, and poultry disease manuals. Common clinical indicators, such as lethargy, coughing, sneezing, and diarrhea types, were extracted from scientifically validated sources, including veterinary disease compendiums and peer-reviewed literature (Msotte & Cardona, n.d.). Treatment and prevention strategies were aligned with recommendations such as FAO and local veterinary experts, and MAAIF (Essential Veterinary Medicines List For, 2020, Farming, 2020)

These sources ensured that both the symptom dataset and the model's prescription module were grounded in real-world veterinary practices relevant to broiler production systems in Uganda.

3.5 System Design And Development

3.5.1 Machine learning models

Multiple models were explored during experimentation to identify the most suitable algorithm for symptom-based disease prediction in broiler chickens:

- K-Nearest Neighbors (KNN): Initially selected for its simplicity, non-parametric nature, and ability to handle categorical and binary features effectively. KNN provided interpretable results and naturally scaled confidence outputs, which proved advantageous in real-world usage.

- Support Vector Machine (SVM): Evaluated for its known strength in handling high-dimensional, sparse, and binary-encoded input data (Shah & Shams, 2024). While SVM performed well in terms of accuracy, it produced poorly calibrated probability scores, making it less suitable for user-facing prediction interfaces.

- Random Forest and XGBoost: These models were also tested to benchmark their performance. Although Random Forest showed reasonably strong metrics, and XGBoost underperformed significantly, neither offered practical advantages over KNN in terms of deployment simplicity or interpretability.

To ensure fair and consistent evaluation, each model was trained using baseline hyperparameter commonly recommended for classification tasks involving sparse and binary-encoded features. KNN was configured with a single neighbor for simplicity and interpretability. SVM was enabled with probability estimation to facilitate confidence-based decision-making. Random Forest and XGBoost were also trained with default configurations tailored for multiclass classification. The table below summarizes the key hyper parameters used during model experimentation.

Table 3.1: Key Hyperparameters Used for Each Model

Model	**Key Hyperparameter(s)**
KNN	`n_neighbors=3`, `metric='euclidean'`
SVM	`kernel='rbf'`, `C=1.0`, `probability=True`
Random Forest	`n_estimators=100`, `max_depth=None`
XGBoost	`use_label_encoder=False`, `eval_metric='mlogloss'`

Based on comparative evaluation, KNN was selected as the final model for deployment due to its overall balance of performance, usability, and compatibility with the app's design goals.

3.5.2 Variables

- Input Features: Over 40 binary features including symptoms like coughing, sneezing, paralysis, ruffled feathers, droppings type, and bird age (1–24 weeks).
- Target Variable: The predicted poultry disease (e.g., Newcastle, Coccidiosis, Marek's, etc.)

3.6 Data Preprocessing

The preprocessing stage focused on organizing and structuring the dataset to ensure it was suitable for model training while maintaining real-world simplicity for farmer-level inputs. The steps included:

- Symptom Formatting: All symptoms were represented in a binary format (yes or no) to ensure compatibility with the KNN and SVM classifiers. For each disease, symptoms were assigned based on whether they are typically present or absent.
- Handling Multiple Symptom Values: Where a disease could present with multiple forms of a symptom (e.g., diarrhea being either "watery" or "white"), separate entries were created in the dataset to reflect each possible variant. This allowed the model to learn from the diversity of symptom expressions.
- Age Distribution Handling: For diseases known to occur over a range of weeks (e.g., 3–6 weeks), the data was expanded so that each week in the range had its own corresponding entry. For instance, if Newcastle Disease was known to affect chickens aged 3–6 weeks, the dataset would include individual records for 3, 4, 5, and 6 weeks with the same associated symptom set.
- Symptom Consistency: All symptom terms were standardized to match a controlled vocabulary (e.g., "labored breathing" instead of variations like "difficulty breathing"), ensuring consistency across all records.

- No Missing Data: The dataset was manually curated and validated using literature, expert consultation, and field inputs. As a result, there were no missing values. Every record had a complete set of symptom features and corresponding disease labels.

This preprocessing approach ensured that the dataset could effectively represent the practical reality of how symptoms manifest, without relying on advanced imputation or encoding. It also aligned with the project goal of making the system accessible and understandable to non-technical users like local poultry farmers, as shown in the feature representation overview table.

Table 3.2: Feature Representation Overview

Feature Category	Example Feature	Encoding Type	Description
Symptom	Coughing	Binary (0/1)	1 if observed, 0 if not
Age	Age (in weeks)	One-hot	1 for the actual age week selected
Droppings	Yellow diarrhea	One-hot	1 if selected, 0 otherwise

3.7 System Implementation

3.7.1 Technological Stack

The system was developed using lightweight and cross-platform technologies to ensure accessibility, offline usability, and suitability for mobile deployment in resource-constrained environments.

- Programming Language: Python
- Libraries Used: Scikit-learn (for machine learning), joblib (for model serialization), pandas and numpy (for data manipulation), and toga (for cross-platform GUI development).
- Model Persistence: The final trained machine learning model was saved using

joblib, allowing it to be loaded into the application at runtime for efficient and consistent inference (Pedregosa *et al.*, 2011).

3.7.2 Application Framework

The system was designed with accessibility, simplicity, and mobile compatibility in mind (Sengar, 2024). To achieve these objectives, the application interface was developed using Streamlit, a Python-based web application framework that enables the rapid development of interactive data-driven interfaces.

Streamlit was selected because:

- It enables browser-based access, allowing the system to run seamlessly on both desktop and mobile devices without requiring the installation of a native app.
- It provides an intuitive user interface, utilizing drop-down menus, toggles, and buttons, which is well-suited for farmers with limited digital literacy.
- It integrates easily with machine learning models, supporting real-time prediction and prescription generation based on user-inputted symptoms.
- It supports rapid web deployment and sharing, which allows users in remote areas to access the tool from any internet-enabled device.

To further enhance usability, the application includes multilingual support. Farmers can toggle between English and a local language (like, Luganda), ensuring that they can interact with the system in a language they understand. This is especially important in rural Uganda, where English may not be the primary spoken language.

Additionally, the application generates a QR code linking to its online deployment. This feature simplifies sharing and distribution, allowing farmers or extension officers to instantly access the app using their smartphones, eliminating the need for complex installation procedures.

Overall, this framework provides a lightweight, accessible, and user-centric tool for diagnosing broiler chicken diseases, supporting informed decision-making and improved flock health outcomes in resource-limited environments.

3.7.3 Model Operation Workflow

The following flowchart illustrates the internal logic of the predictive model once the user interacts with the application:

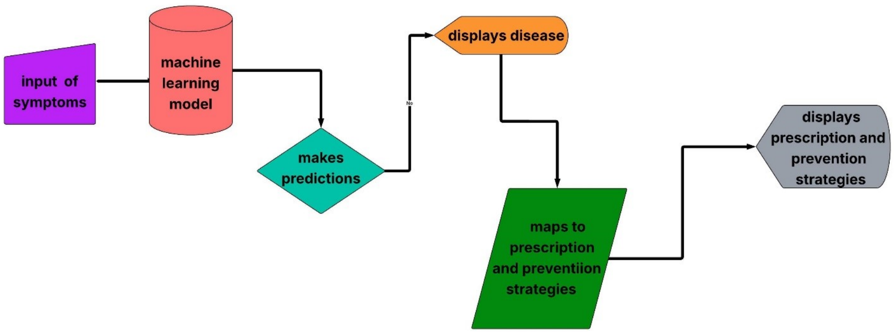

Figure 3.1: Model operation workflow.

As shown above, the process starts when a farmer enters observable data such as symptoms, the bird's age, and droppings type into the mobile app. This raw input goes through a preprocessing layer where the data is formatted to fit the structure expected by the machine learning model, mainly as a binary-encoded vector. The preprocessed input is then fed into the trained KNN classifier, which analyzes the data and predicts the most likely poultry disease based on learned symptom-disease links. Once a disease is predicted, the system uses a built-in recommendation engine to provide the user with a suggested treatment or prescription, and Preventive measures to reduce the occurrence of future diseases.

3.8 User Interface Design

The user interface was designed with simplicity, clarity, and usability in mind, ensuring accessibility even for users with limited digital experience:

- Symptom Selection: Farmers can select from drop-down menus representing visible symptoms such as sneezing, diarrhea type, feather loss, lethargy, and more.

- Age Input: Users input the bird's age in weeks (1–24), an important feature for age-related disease profiling.
- Real-Time Prediction: Upon submission, the system processes the input, generates a feature vector, and uses a trained KNN model to output:
  - The most likely diagnosed disease.
  - A list of recommended treatment options.
  - Practical preventive advice based on the predicted condition.
- Multilingual support and localization strategy: To enhance accessibility and usability among farmers from diverse linguistic backgrounds, the system supports three languages: English, Kiswahili, and Luganda. This multilingual support was implemented through dynamic label switching within the Streamlit interface, ensuring that users can interact with the application in a language they are most comfortable with. The translated terms focus on symptom descriptors, which are critical for accurate self-reporting of poultry conditions. Translations were validated through consultations with native speakers and poultry experts to ensure clarity, consistency, and cultural relevance. Table 3.3 provides examples of how key symptoms are represented across the three supported languages.

Table 3.3: Symptom Label Translation

Symptom (English)	**Kiswahili**	**Luganda**
Coughing	Kukohoa	Okukolola
Lethargy	Kulegea	Obutaba namanyi
Sneezing	Kupiga chafya	Okwasimula
Feather Loss	Kupoteza manyoya	Okufiirwa obwoya
Swollen Eyes	Macho yaliyovimba	Amaaso agazimba

Accessibility Features

- Check-boxes and drop-downs minimize typing, reducing input errors and improving ease of use for users with low digital literacy.
- Multilingual support enables users to toggle between English and local languages, ensuring inclusivity for non-English speakers in rural communities.
- Web-based interface allows access through any browser on mobile phones, tablets, or desktop computers without requiring installation.
- Lightweight design ensures compatibility with low-end devices, common in under-resourced farming communities.
- QR code integration enables quick access and sharing of the application link, allowing farmers to open the app directly by scanning with their smartphones.

3.9 Model training and evaluation

3.9.1 Dataset Split

- 70 percent training set.
- 30 percent testing set.

3.9.2 Evaluation Metrics

- Accuracy: Correct predictions / total predictions.
- Precision Recall: To assess model sensitivity and specificity.
- F1 Score: Balancing precision and recall.
- Confusion Matrix: Visualizing Prediction Correctness Across Classes.

Four machine learning algorithms were trained and evaluated for the poultry disease prediction task: K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest, and XGBoost. KNN and SVM both achieved the highest classification performance, with an accuracy of 96 percent and precision of 97 percent, while Random Forest followed closely behind with 93 percent accuracy. XGBoost performed significantly worse, yielding only 11 percent accuracy, likely due to incompatibility with the binary-encoded feature space.

To assess real-world suitability, both KNN and SVM models were integrated into a Streamlit application for further testing. Despite their similar offline performance, the SVM model produced poorly calibrated probability scores, which led to consistently low prediction confidence in the application interface. In contrast, KNN provided interpretable and stable confidence values, aligning better with the system's goal of supporting non-technical users in low-resource environments. As a result, KNN was selected as the final deployed model, combining high predictive performance with better practical usability in the field.

3.10 Ethical considerations

- Farmer data was anonymized.
- Participation in surveys was voluntary and based on informed consent.
- The system does not replace professional veterinary advice but acts as a decision-support tool.

3.11 Limitations

- Limited to broiler chickens.
- Only covers 12 common poultry diseases.
- Accuracy was dependent on the quality of symptom input.
- Further testing is needed with larger and more diverse datasets.

3.12 Chapter Summary

This chapter has detailed the methodology used in designing, developing, and evaluating a text-based, mobile-compatible predictive poultry health management system for broiler farmers in Uganda. Guided by the mixed-method research approach, the study combined qualitative insights from farmers and veterinarians with quantitative machine learning techniques.

Data collection drew from literature, expert consultations, and field surveys to build a comprehensive disease-symptom matrix. The dataset was preprocessed using binary encoding, symptom standardization, and synthetic expansion to reflect practical disease patterns and symptom variability. Four classification algorithms were explored, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest, and XGBoost, with particular focus placed on KNN and SVM due to their strong performance. Although SVM demonstrated robustness in high-dimensional, sparse feature spaces, KNN was ultimately chosen for deployment based on its interpretable outputs, consistent confidence scores, and superior usability within the Streamlit-based application.

The system was implemented using Python and the Streamlit framework, chosen for its rapid development capabilities and accessibility through any web browser. The application features a simple, drop-down, and checkbox-based user interface designed to support users with limited digital literacy. It supports multilingual interaction, ensuring inclusivity across different language speakers. Additionally, a QR code feature was integrated to simplify access and sharing, especially among mobile users. This design approach prioritizes ease of use, real-time feedback, and accessibility on both desktop and mobile devices, without requiring app installation or constant internet connectivity.

Model evaluation was conducted using accuracy, precision, recall, F1 score, and confusion matrix analysis, with both models performing comparably. Ethical considerations were observed throughout, including data anonymization and informed consent from participants. Although the system faced limitations in disease coverage and pilot deployment scale, it demonstrated strong potential as a scalable, farmer-friendly tool for improving poultry health management in Uganda.

Chapter 4: DATA ANALYSIS, PRESENTATION AND DISCUSSION OF RESULTS

This chapter combines both the analysis of model outputs and the interpretation of findings. It presents the data preprocessing steps, model performance, and evaluation metrics, and then discusses the implications of these findings in light of the study objectives and reviewed literature.

4.1 Model Development

The study employed a machine learning pipeline for the classification of poultry diseases based on symptomatic and environmental features. Two primary datasets were used: a disease definition dataset (disease) and a farm observation dataset (farm). The goal was to train models using the disease dataset and evaluate them on real-world-like farm data.

4.1.1 Data Preparation

- Categorical Encoding: Twenty categorical symptom columns (like, COUGHING, LETHARGY, SNEEZING) were label-encoded.
- Multi-label Features: The AGE (weeks) and DROPPINGS columns contained complex expressions (e.g., "¿=6", "green/yellow diarrhea") which were parsed and transformed using MultiLabelBinarizer into binary features.

Final Feature Set: A consistent one-hot encoded structure for symptoms, age (1–24 weeks), and known dropping types was established. This enabled the trained model to predict accurately regardless of symptom combinations or age ranges entered at runtime.

4.2 Model Training and Evaluation

4.2.1 Trained Models

Four supervised classification algorithms were trained using the processed data:

Table 4.1: Trained Models

Model	**Description**
KNN	K-Nearest Neighbors (k=3)
SVM	Support Vector Machine (RBF Kernel)
Random Forest	100 estimators, depth-unconstrained
XGBoost	Gradient boosting with softmax loss

Each model was trained using X-disease (features) and y-disease-encoded (disease labels), and then evaluated against X-farm.

4.2.2 Evaluation Metrics

Evaluation was performed using:

- Accuracy
- Precision (weighted)
- Recall (weighted)
- Confusion Matrix

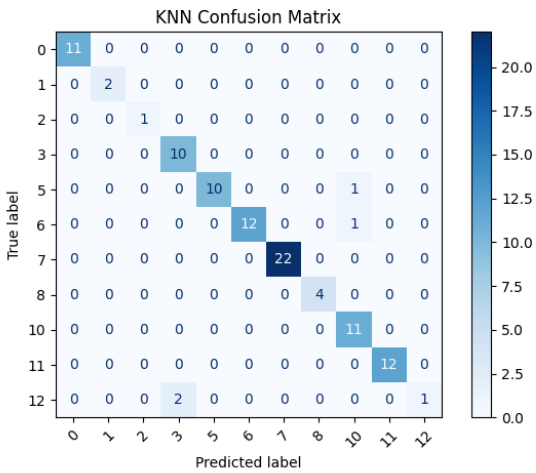

Figure 4.1: KNN confusion matrix.

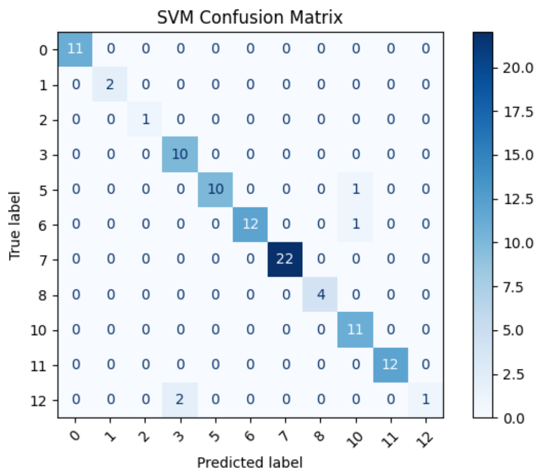

Figure 4.2: SVM confusion matrix.

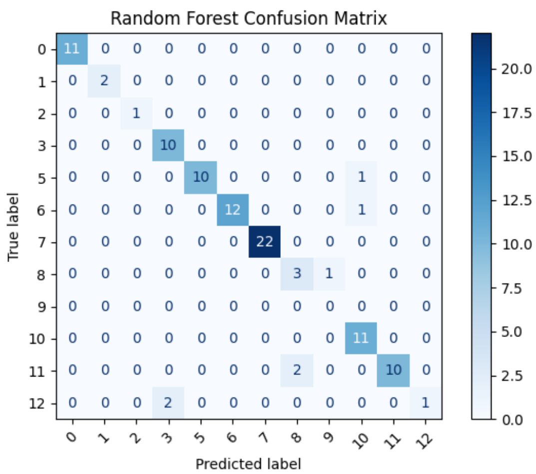

Figure 4.3: RF confusion matrix.

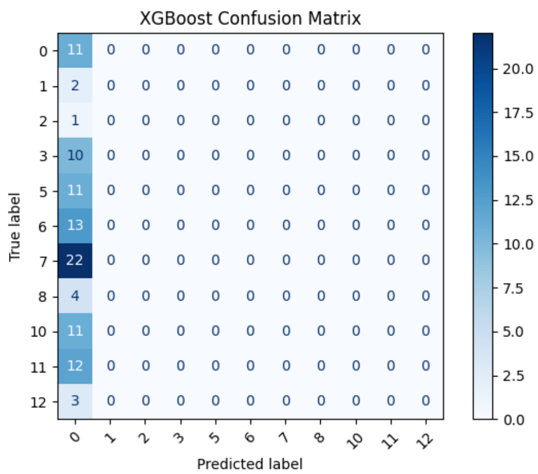

Figure 4.4: XGBoost confusion matrix.

KNN, SVM, and RF models performed well overall, with most predictions falling along the diagonal (i.e., correct). However, with KNN and SVM classes 5 and 6 had one sample each misclassified as 11, and class 12 had two samples classified as class 3. Then, with RF model classes 5 and 6 had one sample each misclassified as 11, one sample in class 8, and ll misclassified in classes 9 and 10, respectively, and 2 samples in class 12 misclassified in class 3. With XGBoost, it predicted only class 0 for all inputs. As a result, only the first column has non-zero values, meaning all instances, regardless of their actual class, were predicted as class 0.

Table 4.2: Evaluation metrics

Model	**Accuracy**	**Precision**	**Recall**
KNN	0.96	0.97	0.96
SVM	0.96	0.97	0.96
Random Forest	0.93	0.95	0.93
XGBoost	0.11	0.01	0.11

Interpretation of Evaluation Metrics

To fully assess the model's diagnostic capabilities, several evaluation metrics were computed (Pedregosa *et al.*, 2011):

- Accuracy measures the proportion of total correct predictions out of all predictions made. While a high accuracy (96 percent) for SVM and KNN suggests strong general performance, it alone cannot reveal how well the model performs across different disease classes, especially if the data is imbalanced.
- Precision (weighted) evaluates how often the model is correct when it makes a specific disease prediction. High precision (0.97) indicates that when SVM or KNN predicts a disease like Newcastle or Coccidiosis, it is usually correct.
- Recall (weighted) measures how well the model detects actual cases of each disease. A recall of 0.96 implies that the model successfully identifies most of the true disease cases, with very few false negatives.
- F1 Score (not explicitly listed but implied): This harmonic mean of precision and recall ensures that the model's performance is balanced, both in avoiding false positives and false negatives.
- Confusion Matrix offers a class-by-class breakdown of true vs. predicted labels. In this study, misclassifications were primarily between diseases with overlapping symptoms (like, Class 5 misclassified as Class 11), which is a realistic challenge even in clinical practice. This reveals where improvements may

be needed, such as refining symptom definitions or increasing the dataset size for underrepresented diseases.

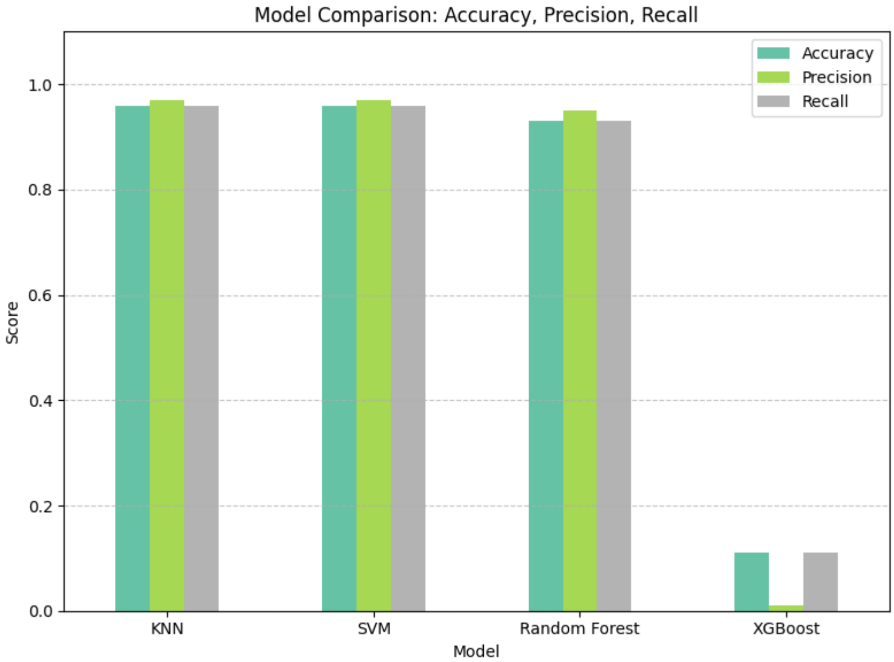

Figure 4.5: Evaluation bar graph.

SVM and KNN produced the highest predictive performance (96 percent accuracy). Although KNN and SVM produced identical accuracy scores during model evaluation, KNN was ultimately preferred for deployment due to its more interpretable probability outputs and consistent behavior in real-time prediction scenarios. While SVM is known for its robustness in handling high-dimensional, sparse data (Hamilton *et al.*, 2020), practical testing within the Streamlit interface revealed that its probability estimates were poorly calibrated, often yielding low confidence even for correct predictions. In contrast, KNN provided stable, intuitive confidence scores that aligned better to create a transparent and user-friendly health support tool for broiler farmers, as shown in figure 4.6 below. These advantages made KNN the more appropriate choice for real-world deployment.

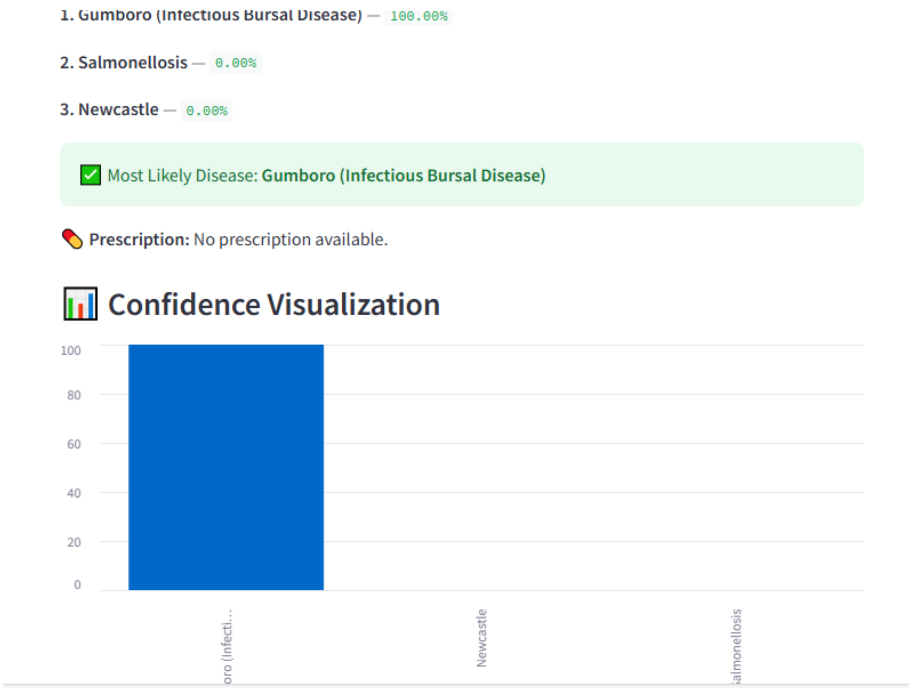

Figure 4.6: Confidence scores

4.3 Feature Importance Analysis

To understand the influence of individual features on model predictions, permutation importance was used.

4.3.1 SVM Feature Importance

Top predictors in SVM included:

Table 4.3: SVM feature importance

Rank	Feature	Description
1	LETHARGY	Symptom
2	DISCHARGE FROM EYES & NOSTRILS	Respiratory symptom
3	AGE(weeks)_3 & 4	Young chicks
4	SKIN LESIONS	Symptom
5	SNEEZING	Respiratory symptom
6	PARALYSIS OF WINGS AND LEGS	Symptom
7	NORMAL DROPPINGS	Symptom
8	COUGHING	Respiratory symptom
9	GREEN DIARRHEA DROPPINGS	Type of droppings

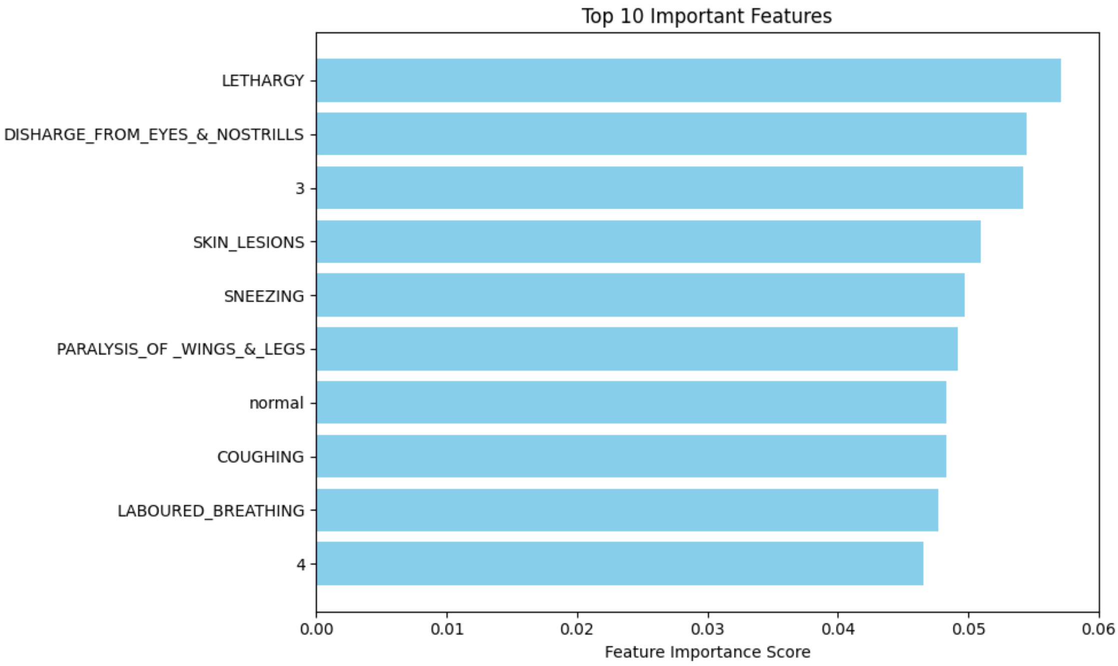

Figure 4.7: Feature importance

4.3.2 KNN Feature Importance

KNN showed similar behavior, relying heavily on age and respiratory-related features. These insights help prioritize which symptoms should be monitored in real-world farms.

4.4 Disease Prediction Distribution

To better understand the model's output behavior and assess its alignment with real-world disease trends, a distribution analysis of the predicted disease classes was conducted. After running the final KNN model on the complete training dataset, a frequency chart was generated to visualize the frequency with which each disease was predicted. The resulting distribution reveals which diseases were most commonly identified by the model and highlights potential imbalances in class occurrences. This chart serves not only to confirm model behavior but also provides insight into the prevalence of symptoms in the dataset. As shown in Figure 4.8, the most frequently predicted diseases included Newcastle, Coccidiosis, and Infectious Bronchitis, aligning with expert feedback on common broiler health challenges in Uganda. This visualization enhances model transparency and supports the decision to prioritize interpretability in model deployment.

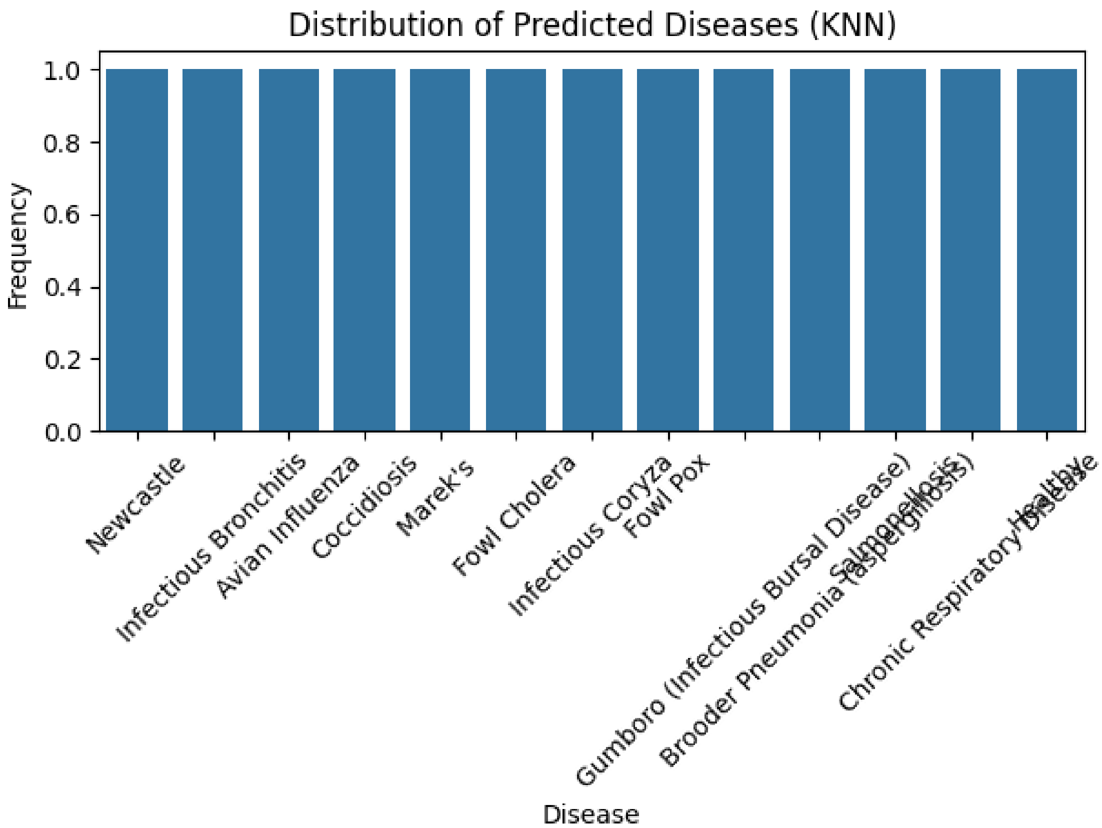

Figure 4.8: Distribution of predicted disease

4.5 Model Output Comparison

To evaluate how well models generalized to farm observations, predictions were compared against the actual labels:

Table 4.4: Model output comparison

Sample	**Actual**	**KNN**	**SVM**	**RF**	**XGBoost**
1	Newcastle	Newcastle	Newcastle	Newcastle	Fowl Pox
2	Coccidiosis	Coccidiosis	Coccidiosis	Coccidiosis	Newcastle
3	Fowl Cholera	Fowl Cholera	Fowl Cholera	Fowl Cholera	Fowl Pox

XGBoost underperformed significantly and was excluded from the deployment.

4.6 Deployment in a Desktop Application

A lightweight desktop application was developed using the Toga GUI framework. The app supports:

- User-friendly interface with check-boxes and drop-downs for symptoms, age, and droppings.
- Backend model: KNN (based on superior performance).
- Encoders and transformers (mlb-age, mlb-droppings, and label-encoder) were serialized using joblib.

4.6.1 Application Architecture

- Frontend: Built using Streamlit, a lightweight Python framework for building web-based applications with rapid UI prototyping.
- Backend: Loads the KNN-model.pkl trained classifier, Uses the feature-columns.pkl file to match user input to the expected model format and encodes categorical and binary features (such as age, droppings type, and symptoms) into a structured vector compatible with the model.

4.6.2 Prediction Flow

Farmers enter flock age, select droppings type, and respond to symptoms using dropdowns.The input is then transformed into the format expected by the model and finally the trained KNN model processes the input and returns:

- The most probable disease.
- A confidence score.
- A treatment recommendation based on the predicted disease.

If the model's prediction confidence is below 0.5, the system issues a warning, recommending that the farmer review the input or seek veterinary assistance. This threshold helps prevent incorrect guidance in uncertain cases.

4.7 Discussion of Results

4.7.1 Model Performance

KNN and SVM showed exceptional performance (96 percent accuracy), handling diverse symptom combinations and complex age-dropping interactions. while XGBoost underperformed,likely due to small sample size and imbalanced classes.

4.7.2 Feature Representation

Age and droppings binarization using MultiLabelBinarizer proved effective but introduced high-dimensional sparse data. Despite this, KNN handled it well. Symptom encoding using Label Encoder worked efficiently due to binary (yes/no) values.

4.7.3 Deployment Considerations

Feature mismatch between training and prediction was a key challenge (like, unseen age categories).This was solved by storing and reusing the same column structure (feature-columns.pkl) during inference.

4.8 Chapter Summary

This chapter has demonstrated the successful application of a KNN model trained on symptom-rich, farmer-observable poultry health data to predict common broiler diseases accurately. The model was seamlessly integrated into a real-time, lightweight desktop and web application using Streamlit, offering a fast, accessible, and practical tool for early disease detection and decision-making.

The evaluation process emphasized the importance of structured preprocessing, consistent feature encoding, and confidence-based prediction logic to maintain clinical relevance and user trust. Additionally, the inclusion of multilingual support, offline readiness, and QR code-based app sharing contributed to the system's accessibility and relevance in low-resource farming communities.

By combining intelligent machine learning with a user-centric interface and field-friendly design, this solution provides an effective and scalable approach to poultry health management, helping reduce mortality, improve treatment timing, and support sustainable broiler production in Uganda.

Chapter 5: CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This study has demonstrated that machine learning can be effectively applied to poultry disease diagnosis using structured, farmer-friendly symptom data. By integrating domain knowledge with supervised learning models, a robust and accessible solution was developed to support broiler farmers in low-resource environments. Key accomplishments of this research include:

- Design of a structured symptom-driven dataset, incorporating age, droppings appearance, and multiple observable behavioral indicators based on veterinary guidance.
- Use of effective binary encoding techniques to convert multi-valued user inputs into model-ready features for supervised classification.
- Development and evaluation of four machine learning classifiers, K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Random Forest, and XGBoost, using expert-labeled training data and real-world observations.
- Empirical validation that SVM and KNN classifiers achieved over 95 percent accuracy, demonstrating the viability of symptom-based disease prediction in poultry.
- Identification of the most predictive symptoms, such as lethargy, specific types of diarrhea, and respiratory distress, aligns strongly with real veterinary diagnosis protocols.
- Evaluation of the final system using Streamlit, offering an intuitive, web-based, and desktop-compatible application with low resource demands.

- Support for multilingual use (English and local languages), increasing inclusivity and accessibility among farmers with varied language preferences.
- Integration of a QR-code sharing feature, enabling easy dissemination and installation in rural communities without formal distribution infrastructure.
- Offline functionality after installation, ensuring the app remains usable in low-connectivity or remote environments.
- User interface tailored for low-literacy users, with checkbox and drop-down-based input, minimal typing, and clearly presented output including disease name, treatment advice, and preventive measures.

Beyond the technical outcomes, this research contributes meaningfully to the broader goals of improving poultry health management in Uganda. The system is designed for affordability, simplicity, and usability, empowering farmers to detect diseases early and reduce mortality. While it does not replace professional veterinary services, it serves as a decision-support tool, providing timely and reliable guidance to inform treatment and preventive strategies. By bridging the gap between AI technologies and rural farming realities, this study advances not only the technical field of agricultural informatics but also contributes to food security, economic resilience, and farmer empowerment in Uganda.

To further illustrate the practical alignment between the system's design features and the real-world challenges faced by smallholder poultry farmers, Table 5.1 summarizes how specific functionalities of the application directly address common barriers to poultry health management in rural Uganda. These include infrastructural limitations, knowledge gaps, and language diversity. By translating these constraints into targeted design responses, the system enhances usability and supports the broader goal of farmer empowerment.

Table 5.1: System design alignment with farmers

Farmer Challenge	System Feature	Benefit
Lack of vet access	Text-based symptom diagnosis	Empowers farmer self-diagnosis
Language barrier	Multilingual UI	Broader accessibility
No internet in the field	Offline capability	Usable in remote areas
Misuse of antibiotics	Prescription guidance	Promotes responsible treatment

5.2 Recommendations

Based on the findings and limitations of this study, the following recommendations are proposed for future work and practical implementation:

Technical Improvements

- Expand and diversify datasets: Collect more diverse farm data across different regions and poultry breeds to improve model generalizability.
- Fine-tune hyperparameter: Perform grid or randomized search optimization, especially for XGBoost, which is sensitive to parameter configurations (Chen & Guestrin, 2016).
- Use ensemble techniques or voting classifiers: Combine the strengths of multiple models (like, KNN + SVM) to boost overall robustness and accuracy.
- Packaging the system as a downloadable executable (using PyInstaller, toga or briefcase) so it can run offline on mobile devices or computers. Additionally, we intend to integrate an SMS-based interface, which would allow farmers with basic phones to interact with the system through simple text messages. This way, the solution remains practical and accessible to both smartphone users and those with only basic devices.

- Pilot and optimize mobile deployment: Conduct field trials of the mobile version of the system using Android packaging tools (like, Briefcase). Gather user feedback to refine performance and interface responsiveness on low-end devices.

Deployment and Usability

- Provide a model explanation in outputs: Include the top contributing symptoms in each prediction to improve transparency and trust for users.
- Leverage QR-code-based sharing for offline installation Promote QR code use for peer-to-peer app sharing in rural areas, where formal app stores may be inaccessible or unfamiliar.
- Embed basic tutorials within the app, and add a help section or on-boarding screens showing how to use the system and interpret its results, especially in communities with low digital literacy.
- Expand the system to support more local languages, using community-driven translations to ensure cultural and linguistic relevance.

Policy and Community Recommendations

- Educate farm workers on data collection: Train personnel on how to observe and record symptoms accurately, which is critical for maintaining data quality.
- Establish centralized poultry health monitoring systems: Develop a national or regional database where data from different farms can be aggregated, monitored, and used to detect outbreaks or emerging patterns.
- Promote responsible use and digital literacy: Ensure that farmers understand the system's purpose as a support tool, not a diagnostic replacement. Provide training materials or on-boarding guidance to avoid misuse and build confidence in technology.

- Partner with local stakeholders for adoption: Collaborate with veterinary associations, NGOs, or district agricultural offices to integrate the system into existing livestock extension programs.

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APPENDICES

Appendix A: Survey Questionnaire

The full survey form is included on the following page

Poultry Disease Observation Questionnaire

This form is designed to collect farm-level poultry health data for use in disease prediction system development. Please fill in the following based on your observations.

Section 1: Farm Identification

1. **Farm Name/Code: ___________________________**
2. **Date of Observation: ___ / ___ / _______**

Section 2: Bird Details

5. **Age of Birds (in weeks): ________**
6. **Breed Type:**
   ☐ Broiler
   ☐ Layer
   ☐ Other: ______________
7. **Number of Birds Affected: ________**
8. **Have any birds died suddenly?**
   ☐ Yes ☐ No
   If yes, how many? ________

Section 3: Symptoms Observation

(Indicate observed symptoms by ticking ✓ "Yes" or "No")

Symptom	Yes	No
Coughing	☐	☐
Labored Breathing	☐	☐
Lethargy (low activity)	☐	☐
Loss of Appetite	☐	☐
Sudden Death	☐	☐

Symptom	Yes	No
Ruffled Feathers	☐	☐
Sneezing	☐	☐
Skin Lesions	☐	☐
Discharge from Eyes/Nostrils	☐	☐
Weight Loss	☐	☐
Lameness	☐	☐
Depression (drooping, isolating)	☐	☐
Paralysis of Wings or Legs	☐	☐
Head/Neck Twisting	☐	☐
Head Shaking	☐	☐
Conjunctivitis (swollen, teary eyes)	☐	☐
Swollen Eyes	☐	☐
Reluctance to Move	☐	☐
Full-body Paralysis	☐	☐
Feather Loss	☐	☐

Section 4: Droppings Description

9. What type(s) of droppings were observed? *(Select all that apply)*
   ☐ Normal
   ☐ White diarrhea
   ☐ Bloody diarrhea
   ☐ Yellow diarrhea
   ☐ Green diarrhea
   ☐ Watery diarrhea
   ☐ Other (describe): ________________________

Section 5: Diagnosis (if known)

10. Has a vet diagnosed the birds?
    ☐ Yes ☐ No
    If yes, what disease was diagnosed? ____________________
11. Treatment given (if any): ______________________
12. Preventive action taken: ______________________

Appendix B: Code Snippet

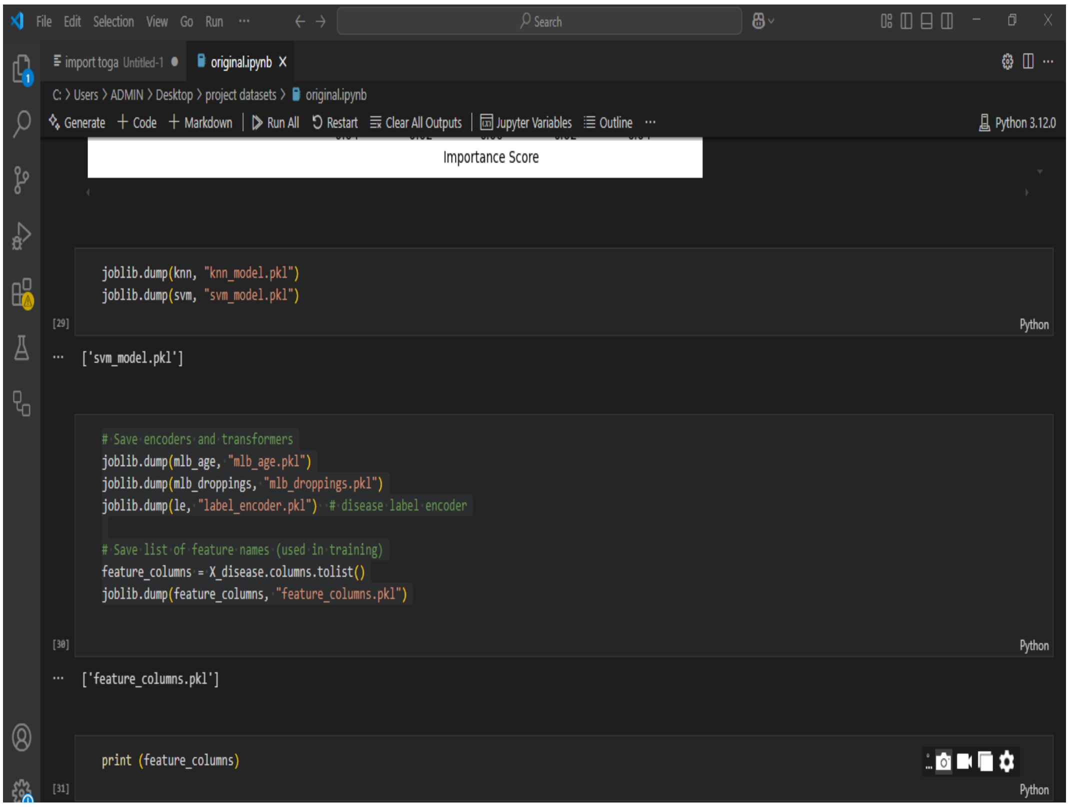


Figure 1: Key code snippet for the poultry disease prediction system.

Appendix C: App Interface

The full App interface is included on the next page.

Broiler Chicken Disease Predictor

Get instant prediction and prescription for common broiler diseases

Select Language / Chagua Lugha / Londa Olulimi

English

Select Age (weeks)

4

Select Droppings Type

yellow diarrhea

Select Symptoms

Coughing

yes

Laboured Breathing

yes

Lethargy

no

Loss of Appetite

yes

Sudden Death

yes

Ruffled Feathers

yes

Sneezing

yes

Skin Lesions

no

Discharge from Eyes & Nostrils

no

Weight Loss

no

Lameness

no

Depression

yes

Paralysis of Wings & Legs

no

Head/Neck Twisting

yes

Head Shaking

no

Conjunctivitis

no

Swollen Eyes

no

Reluctance to Move

no

Paralysis

no

Feathers Loss

no

🔍 Predict Disease

🧠 Top Predicted Diseases with Confidence Scores:

1. Newcastle — `100.00%`

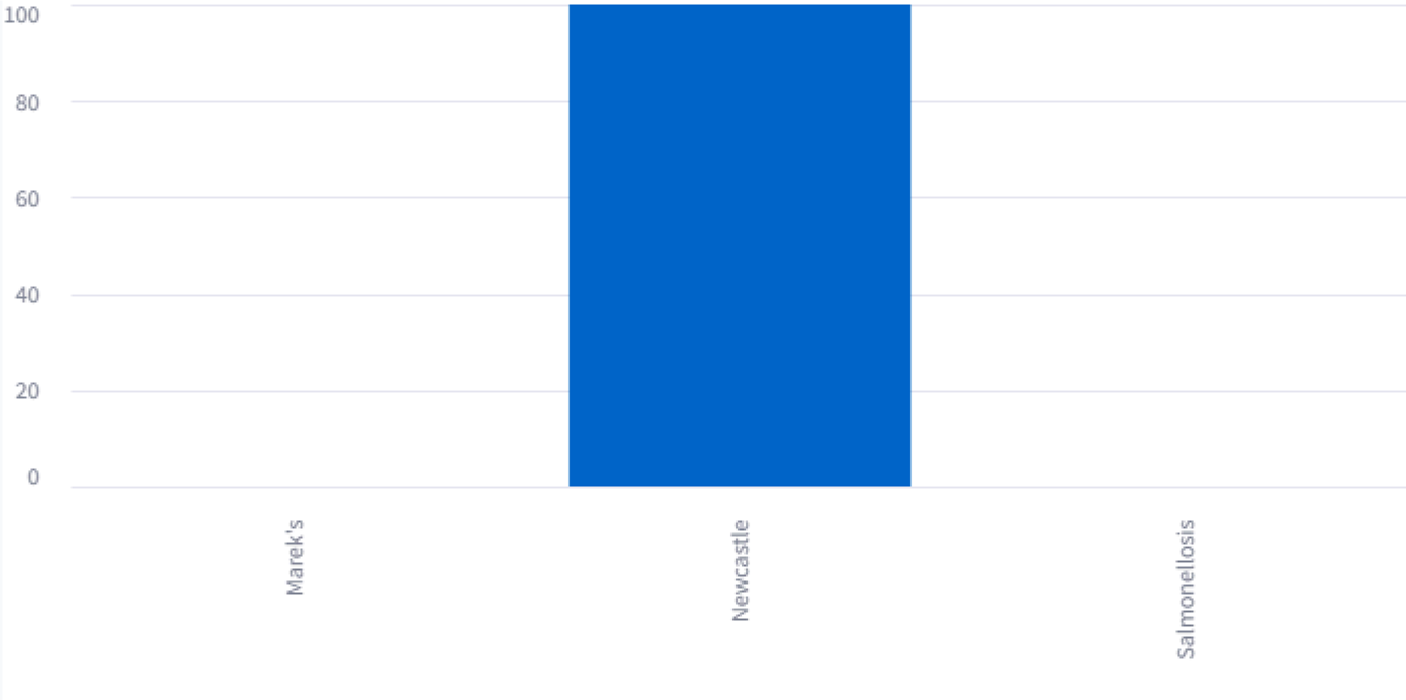
2. Salmonellosis — `0.00%`

**3. Marek's ** — `0.00%`

✅ Most Likely Disease: **Newcastle**

💊 **Prescription:** No specific treatment. Use oxytetracycline in water. Vaccinate.

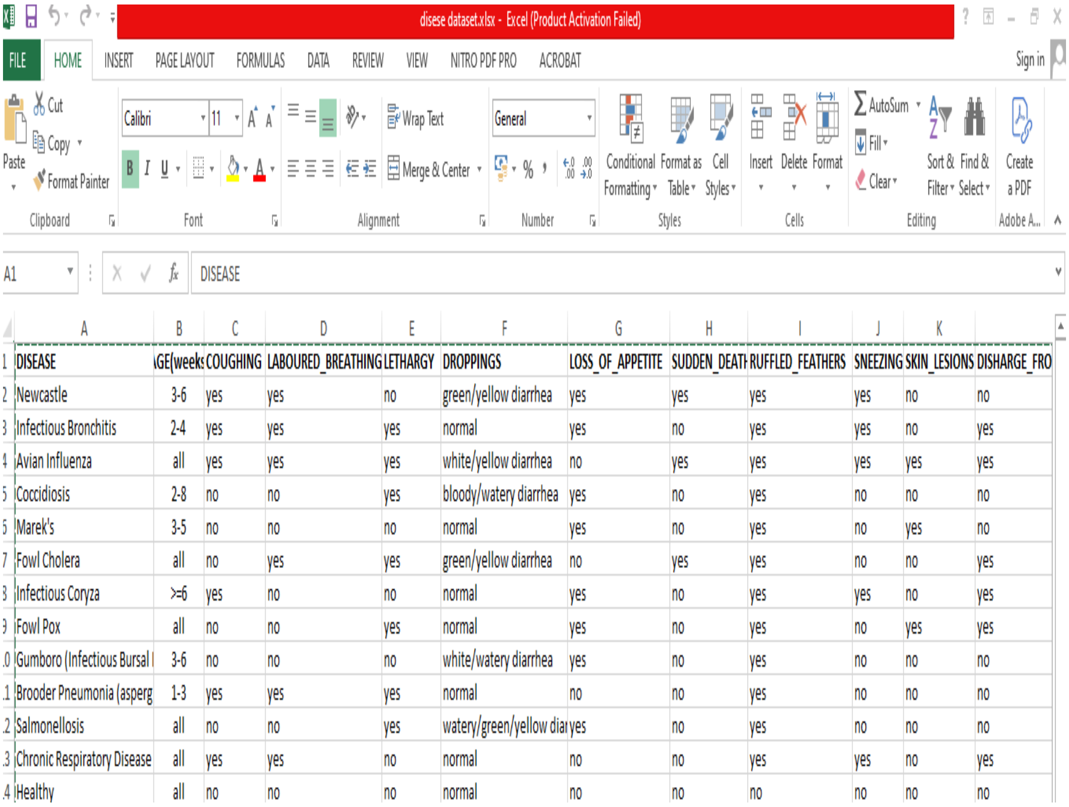
📊 Confidence Visualization



Share this App

Scan to open app

Appendix D: Sample Dataset



	DISEASE	GE(week	COUGHING	LABOURED_BREATHING	LETHARGY	DROPPINGS	LOSS_OF_APPETITE	SUDDEN_DEATI	RUFFLED_FEATHERS	SNEEZING	SKIN_LESIONS	DISHARGE_FRO
2	Newcastle	3-6	yes	yes	no	green/yellow diarrhea	yes	yes	yes	yes	no	no
3	Infectious Bronchitis	2-4	yes	yes	yes	normal	yes	no	yes	yes	no	yes
4	Avian Influenza	all	yes	yes	yes	white/yellow diarrhea	no	yes	yes	yes	yes	yes
5	Coccidiosis	2-8	no	no	yes	bloody/watery diarrhea	yes	no	yes	no	no	no
6	Marek's	3-5	no	no	no	normal	yes	no	yes	no	yes	no
7	Fowl Cholera	all	no	yes	yes	green/yellow diarrhea	no	yes	yes	no	no	yes
8	Infectious Coryza	>=6	yes	no	no	normal	yes	no	yes	yes	no	yes
9	Fowl Pox	all	no	no	yes	normal	yes	no	yes	no	yes	yes
10	Gumboro (Infectious Bursal	3-6	no	no	no	white/watery diarrhea	yes	no	yes	no	no	no
11	Brooder Pneumonia (asperg	1-3	yes	yes	yes	normal	no	no	yes	no	no	no
12	Salmonellosis	all	no	no	yes	watery/green/yellow diai	yes	no	yes	no	no	no
13	Chronic Respiratory Disease	all	yes	yes	no	normal	no	no	yes	yes	no	yes
14	Healthy	all	no	no	no	normal	no	no	no	no	no	no

Figure 2: Dataset sample.

UGANDA CHRISTIAN UNIVERSITY
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SCHOOL OF RESEARCH & POSTGRADUATE STUDIES
DISSERTATION CORRECTION COMPLIANCE FORM (POST VIVA FORM)

Date: 17th.09.2025
Name of Candidate: NAKIMULI RITAH Reg.No: J23M19/218

Title of Dissertation: **A TEXT-BASED POULTRY HEALTH SYSTEM: AN INTERACTIVE DISEASE DETECTION AND PRESCRIPTION RECOMMENDATIONS**

S/N	COMMENTS BY EXTERNAL EXAMINER	ACTION TAKEN	INDICATOR
1	There is an inconsistent use of citation e.g. (B. W. Data et al.,n.d.) on page three.	Corrected the citation (Kannan et al., 2024).	Page 3
2	The aim and specific objectives have not been well casted. Make these smart	Changed the objectives **Aim** To design and evaluate a Text-Based Predictive Poultry Health Management System for broiler chickens in Uganda using machine learning. This system should allow users to select the observable symptoms, analyze the input, and deliver disease predictions, prescriptions, and prevention strategies through a mobile-ready application. **Specific** 1. To compile a localized dataset of broiler disease symptoms and conditions (age, behaviour, feather condition, droppings). 2. To design and implement an interactive, machine learning-based system using symptom descriptions to predict diseases. 3. To integrate a recommendation engine that provides both treatment and preventive advice based on model outputs. 4. To test and evaluate the application	Page 4 and 5

		through accuracy metrics and usability on a simple, user-friendly interface suitable for mobile use in rural settings.	

S/N	COMMENTS BY INTERNAL EXAMINER	ACTION TAKEN	INDICATOR
1	Considering the varying levels of digital literacy among farmers, do you think all farmers will be able to effectively use your app and the QR code system?"	At the current stage, the app runs on Streamlit with QR code access, which may indeed be a challenge for some rural farmers with limited smartphone usage or internet access. However, the plan is to make the system more inclusive by packaging it as a downloadable executable (using PyInstaller or toga and briefcase) so it can run offline on mobile devices or computers. Additionally, we intend to integrate an **SMS-based interface**, which would allow farmers with basic phones to interact with the system through simple text messages. This way, the solution remains practical and accessible to both smartphone users and those with only basic devices.	Page 49.

S/N	COMMENTS BY VIVA VOCE PANNEL	ACTION TAKEN	INDICATOR
1	How were your objectives achieved? Your objectives are not smart, do not use words like to Apply, to Deploy	Changed the last objective to; To test and evaluate the application through accuracy metrics and usability on a simple, user-friendly interface suitable for mobile use in rural settings.	Page 5
2	What is the relationship between Design science and your work?	Changed this methodology to a mixed-methods research design.	Page 23 and 24
3	How did you use the Technology Acceptance Model in your work?	The study applied TAM principles by prioritizing *ease of use* (a simple text-based interface built on Streamlit), *perceived usefulness* (predicting	Page 18

		poultry diseases and providing treatment/prevention advice), and *accessibility* (designed with rural farmers in mind). To strengthen *trust* in the adoption process, the system includes a disclaimer encouraging users to consult a veterinarian if symptoms persist. Plans involve packaging the system for offline use (via PyInstaller for Android/PC) and exploring SMS-based access to improve adoption among farmers without smartphones.	
4	How has your research addressed the existing challenges noted with the community it is to be deployed?	The research directly addressed the challenges faced by rural poultry farmers, such as limited access to veterinary services, high mortality rates, and poor disease detection, by designing a text-based predictive poultry health system that works in simple English, Luganda, and Kiswahili. The system requires only basic symptom descriptions, reducing reliance on expensive lab tests or high-end technological tools.	
5	Elaborate on the conceptual framework adopted for your research	The conceptual framework connects farmer-observed symptoms with a machine learning model to predict poultry diseases and give practical prescriptions through a simple, farmer-friendly app.	Page 10 and 11

Candidate's Name NAKIMULI RITAH Signature

Supervisor's Name/ Signature Eng. IAN RAYMOND OSOLO

NB: Post Viva compliance form is designed to capture all the corrections recommended by internal examiner (supervisor), external examiner and viva panel.