

A Hybrid Machine Learning Framework for Poultry Disease Prediction and Sustainable Organic Control in Precision Poultry Farming

Akinsola Adeniyi.F¹., Sokunbi.M.A², Ogundele, I.O³, Onadokun I.O⁴., ⁵Wasiu K.O⁵

^{1,2,3,4,5} Yaba College of Technology, Computer Tech. Dept., Yaba, Lagos Nigeria.

Correspondence Author: akinsolafun@gmail.com.

Abstract

Poultry is a vital component of both the world's food supply and agricultural-based economy, especially in developing nations. In many developing nations, poultry is an important source of affordable protein and income for families; however, poultry continues to be challenged by infectious disease agents (e.g., Newcastle Disease, Avian Influenza, Coccidiosis, Salmonellosis). The early detection of these infectious agents and the use of preventative measures are critical to limiting mortality rates, economic loss and reliance on antibiotics. This research presents an integrated machine learning model to predict poultry diseases based on a combination of the environmental and managerial parameters in conjunction with organic methods of disease control. The four machine learning classifiers — Random Forest, Decision Trees, Naive Bayes, and K-Nearest Neighbors (KNN) — were tested and compared using a dataset from a poultry farm that included some factors such as temperature, humidity, litter moisture, bird density, feed quality, and whether or not birds had been vaccinated. Performance metrics for each model are presented through accuracy, precision, recall, F1 score and AUC scores. The experimental findings indicate that a random forest model produced the best predictive accuracy with 94% and a best AUC score of .96. The feature importance indicated that the top predictor for poultry disease were the temperature, humidity, vaccination status and litter moisture. In addition, the proposed sustainable poultry farming system will use predictive modeling to make recommendations for treating poultry disease organically and reduce the need for antibiotics in poultry production. Results show that using sustainable agriculture methods combined with machine learning (ML) techniques can greatly increase the accuracy of poultry disease detection and poultry farm decision-making. This method can be added to existing precision livestock farming systems as well as to mobile decision support tools to allow for real-time monitoring of poultry health.

Keywords: Poultry Disease Prediction, Machine Learning, Random Forest, Precision Livestock Farming, Sustainable Agriculture, Organic Disease Control

1.INTRODUCTION

Poultry production has grown into one of the fastest growing livestock sectors globally and helps meet some of the world's need for food, provides income for rural residents, and serves as an important tool for economic growth. The majority of the global population relies on poultry (eggs and chicken) for high quality proteins and minerals at a relatively low cost. In Nigeria and across much of Africa, poultry production is one of the largest agricultural sectors providing support to both small scale and large scale producers.

Although poultry is an economically important segment of agriculture, it is still susceptible to infectious disease that could result in significant loss of life and also be a major contributor to economic hardship for farmers. Among many other potential causes of illness to poultry; some of the most common causes of disease include; Newcastle disease, Avian Influenza, Infectious Bronchitis and Coccidiosis. The above mentioned diseases spread quickly in high-density bird housing which is typical of all commercial poultry operations; therefore it is essential that these diseases are detected and prevented early in order to maintain healthy flocks and maximize their productive capacity.

Traditional disease detection for poultry has been reliant upon the visual observations of the farmer or veterinarian who are observing the flocks for changes in the animals' behaviors (e.g., abnormal droppings, lethargic behavior, breathing difficulties, decreased food intake) which indicate that a disease is present. The problem with relying on the presence of these observable signs is that the disease could be widespread throughout the flock before the farmer or veterinarian notices them. Although laboratory tests for diagnosing poultry diseases do provide an accurate diagnosis, they take time, money and access to laboratories which can make it difficult for smallholder farmers to obtain reliable diagnoses.

"Artificial Intelligence (AI) and Machine Learning (ML) advances have generated a wide range of ways to improve livestock health monitoring systems. Machine learning algorithms can identify patterns within large and complex data sets that are based on multiple variables including the environment, management practices on the farm and the physical condition of the animals to predict when an outbreak is likely to occur. Benos et al., 2021; Liakos et al., 2018. The predictive model will generate an alert allowing farmers to take preventative action early enough to limit the area where the disease will be located."

Precision livestock farming has increased these capabilities with technology that provides continuous automatic data

collection for monitoring of all aspects of the environment in which the animals are housed. Rowe et al., 2019; Kamilaris & Prenafeta-Boldú, 2018. With sensors, cameras and IoT (Internet of Things) devices the various environmental parameters of temperature, humidity, ventilation, feeding and activity levels of the birds can be continually monitored. The machine learning models can then use this data to identify anomalies in the data and predict the likelihood of future animal health issues.

Many studies that utilized machine learning models to predict diseases in animals, however, these studies primarily focused on the early detection of diseases and not on linking predictive analytics to actual disease management practices. The growing concern over antimicrobial resistance has also created a demand for alternative methods of controlling disease using antibiotics sustainably.

The proposed study is a development of an organic disease control approach which integrates both predictive disease monitoring systems using machine learning with organic treatment recommendations; it represents an integration of two different approaches toward improving sustainability in poultry production. Therefore, the proposed study seeks to develop an integrated hybrid framework that supports both early disease detection through predictive analytics, and environmental responsibility through sustainable disease management approaches. The proposed framework will provide both early detection and treatment of disease in poultry as well as support environmentally friendly methods of poultry farming.

The specific objectives of this research are to:

1. Develop machine learning models for poultry disease predictions based on environmental and farm management data.
2. Determine how different classification algorithms perform in terms of prediction of poultry disease.
3. Identify what factors pose a high risk to poultry disease occurrence.
4. Integrate organic disease management strategies into disease prediction models.

2. Review of Related Areas

The use of digital technology and artificial intelligence for agricultural applications has increased dramatically in the last few years. Specifically, there has been an increase in the application of digital technology and artificial intelligence for health monitoring in livestock. Due to higher levels of demand for poultry products and increasing stocking density levels, poultry farming systems have become more complex. In response to this complexity, researchers have identified the need to implement new technological approaches to monitor poultry health and predict disease outbreaks. Such technological approaches include machine learning, precision livestock farming, and intelligent monitoring systems.

2.1 Precision Livestock Farming and Poultry Monitoring

The term "precision livestock farming" (PLF) refers to the application of technology; including sensor devices, computerized monitoring systems and advanced data analysis tools to continually monitor animal health and behavior, in addition to the productivity of animals in real-time. The

continual monitoring capabilities of PLF allow farmers to constantly monitor environmental conditions and behavioral factors that may affect an animal's overall health. According to Rowe, Dawkins, and Gebhardt-Henrich (2019); there are several ways that new technologies for precision livestock can be used to improve poultry farms through the ability to identify and detect animal health issues before they become severe and/or chronic and provide improved decision-making capabilities for poultry producers.

Environmental variables including; Temperature, Humidity, Air Quality and Litter Moisture are important factors that affect the incidence of disease in Poultry. The poor environment that exists due to poor environmental conditions will provide an ideal environment for Pathogens to survive in, which increases the likelihood of Disease being transmitted throughout a Poultry House. A sensor based system for monitoring environmental parameters allows for the continuous collection of data on environmental conditions, which may be used to develop predictive models for disease in poultry (Benos et al., 2021).

The integration of PLF technologies with machine learning algorithms has further enhanced the ability to detect abnormal patterns associated with disease outbreaks. Automated monitoring systems can collect large volumes of data that can be analyzed using predictive models to identify early warning signs of disease outbreaks before visible symptoms appear.

2.2 Machine Learning Uses for Poultry Disease Prediction

Machine learning is a valuable tool that is being used by many in the field of agricultural data analysis because it allows the processing of large, complex data sets. Machine learning algorithms may be able to predict the risk of diseases in poultry based on the use of various environmental factors, animal health factors and management factors.

Several classification techniques have been utilized for predicting diseases in animals. Algorithms including Random Forest, Decision Trees, Support Vector Machines, and K-Nearest Neighbor were selected as they can handle complex agriculture data sets (Abubakar et al. 2025) and identify non-linear relationships among variables, or patterns within a dataset which could go unobserved with traditional statistical analysis.

Random Forest models are being used to make predictions about diseases as well as other applications in agriculture because they utilize many decision trees to improve both model accuracy as well as predictability. In addition to improving model accuracy and predictability, Random Forest utilizes an ensemble learning approach to reduce the likelihood of a model to be overfit. Overfitting is often caused by large or complex data sets, which can negatively affect how well a model generalizes its results (Paula de Freitas Curti et al., 2023). Decision Trees are another type of model that are commonly used in agricultural applications due to their interpretability and simplicity. Decision Trees create a tree-like structure of classification rules, which makes it easier for farmers or other decision-makers to understand the decision-making process. While Decision Trees are easy to understand, they may suffer from overfitting if the data set is small.

Naive Bayes methods have become popular for disease classification because they provide an efficient and computationally cheap probabilistic method of classification. While the Naive Bayes models assume that all feature values

are independent of each other, they can be very effective at solving many different types of classification problems, especially those related to agricultural data sets. The K-Nearest Neighbor (KNN) method uses the concept of similarity among the data points to classify new data into one of predefined classes. A data point is classified by assigning a class label based on the majority class label of its k-nearest neighbors. KNN has been successfully applied to numerous classification problems, such as identifying disease in livestock.

2.3 Advances of Artificial Intelligence and Computer Vision for Automated Health Monitoring of Poultry Using Images

In recent years, artificial intelligence has given rise to an increasing number of novel approaches to automate poultry health monitoring through use of computer vision technology. Techniques in computer vision, such as deep learning models including convolutional neural networks (CNNs), are being utilized to analyze images of poultry to determine presence of disease symptoms from visual characteristics. Computer vision-based systems provide ability to monitor poultry behavior, changes in posture or visible physical signs of disease. Many computer vision-based systems utilize cameras mounted within poultry houses to provide continuous poultry monitoring and automatic detection of poultry health problems (Kamilaris & Prenafeta-Boldú, 2018; Liu et al., 2023).

Deep learning (DL) has also achieved promising results in image-based disease detection systems that can analyze poultry fecal images to detect disease indicators by identifying color change and/or abnormality of patterns. However, DL requires a large amount of data and significant computational resources; thus, traditional machine learning (ML) may be a more feasible alternative in many agricultural applications with structured databases.

2.4 Sustainable Poultry Disease Management

Beginning with sustainable poultry disease management, there is an emerging body of evidence showing that the continued use of antibiotics for conventional disease prevention/management methods may pose an unacceptable risk to both public and animal health as well as contribute to increasing levels of AMR. The reliance of most of these disease management practices on antimicrobial products contributes to the spread of antibiotic-resistant pathogens.

The excessive application of antibiotics as a measure of controlling infections in livestock increases the rapid emergence of antibiotic-resistant bacteria, which can cause severe public and animal health issues. Studies indicate that the overuse of antibiotics in the production of meat poultry is an important factor for the transfer of drug resistance along the food chain (World Health Organization; Manyi-Loh et al., 2017). As such, it has been increasingly emphasized to develop alternative sustainable methods of controlling diseases in poultry.

Organic and sustainable methods of managing diseases in poultry — which include using herbs or other botanicals; adding probiotics; improving how you manage manure and sanitation; and implementing on-farm biosecurity measures — help promote the natural immunity of chickens while also reducing the amount of environmental factors (like cold

temperatures) that can cause disease to be transmitted among your flock (FAO, 2013).

Of all of those types of organic/sustainable methods of controlling disease in poultry, one is key to keeping your flock healthy — managing their litter. Litter that has too much moisture or contaminants creates an environment that favors pathogens. As a result, when the litter is poor there is an increased chance that bacteria, viruses and parasites will infect the birds in your flock. In fact, research studies have demonstrated that if you are able to provide a good supply of dry, sanitary bedding (i.e., “litter”) you will greatly decrease the number of pathogens present in your poultry system as well as the likelihood of disease developing in your flock (Ritz et al.; Dunlop et al.).

2.5 Research Gap

While much is being done to apply machine learning methods to detect diseases in animals, there are still many areas of study that need to be addressed. While many of the previous studies have focused primarily on detecting a disease as opposed to predicting the occurrence of a disease, this has limited them from providing useful information to early intervention or prevention of disease. In addition to this limitation, few studies have integrated predictive models with disease management strategies that are environmentally friendly or sustainable.

While many studies have concentrated on detecting diseases using images and/or environmental conditions separately from each other, the majority of those studies do not use an integrated framework which uses both types of data to make predictions about disease. Therefore, a combination of machine learning prediction (to predict and identify the presence of disease) and organic disease management strategies (to treat the disease), could lead to a much more holistic method of managing poultry health. Thus, in this study we propose a hybrid model which combines the machine learning based prediction of disease with organic treatment advice. The goal of our proposed system is to be able to detect disease as early as possible, and at the same time promote sustainable poultry farming practices.

3. Methodology

3.1 Data Collection

The data utilized within this research project were obtained from a variety of sources including poultry farm data collected by environmental monitoring systems and farm management records. The variables included in this dataset include: Temperature, Humidity, Moisture content in the litter, Stocking density, Quality of feed, Hygiene of water supply, Vaccination status of birds, Age of birds, Biosecurity practices at the farm level.

3.2 Data Preprocessing

After collecting the Poultry Farm Dataset, it went through a preprocessing phase to ensure data quality and therefore model performance. The preprocessing phase included; handling missing values, standardizing/normalizing the numerical variables and feature selection of factors associated with poultry health and the environment. After

preprocessing, the clean dataset was split into a training set and test set with an 80%:20% split. The preprocessing phase ensured that the dataset was uniform, removed as much noise from the data as possible and increased the dependability and accuracy of the machine learning models that were to be used to predict diseases in poultry.

3.3 Machine Learning Models

Random Forest

Random forest is an Ensemble Machine Learning Technique That Uses Multiple Decision Trees to Increase Prediction Accuracy. It Reduces Overfitting through Averaging of the Predictions from Multiple Trees. It Is Effective at Handling Complex Datasets (Benos et al., 2021; Curti et al., 2023).

Decision Tree

Decision Tree is Classification Algorithm Which Splits Data Based on Feature Conditions to Create a Tree Structure. It Is Easy To Interpret and is Widely Used In Decision Support Systems.

Naive Bayes

Naive Bayes is a probabilistic classifier based on Bayes' theorem. The Naive Bayes classifier also assumes independent feature distributions. This means that Naive Bayes classifiers are particularly well-suited for large datasets where computing the full joint distribution would be computationally infeasible.

K-Nearest Neighbor (KNN)

The K-Nearest Neighbor (KNN) algorithm is a type of supervised learning algorithm; it uses a training set to classify new examples into one of two or more classes. For each example in the training set, it calculates how close it is to a new example. Then, for each example in the training set, the KNN algorithm looks at the K most similar ones to find the most common class label among them. Since KNN is based on distance, it can only be used with continuous attributes. Therefore, all nominal variables in the problem domain must first be encoded as numeric. One of the biggest advantages of KNN is that it is very easy to implement. However, it is not always the best algorithm for every problem because it is based entirely on similarity rather than relevance. This makes it less effective for problems such as identifying patterns in a dataset. (Cover, T., & Hart, P. (1967).

3.4 System Architecture

The proposed system architecture combines organic poultry disease management and a machine learning disease prediction component.

Layer 1: Data Collection Layer

layer collects all data from the environmental sensors in combination with the records of management of the poultry farms and all observations relating to poultry health.

Layer 2: Data Processing Layer

layer processes all data collected in layer 1. Data processing includes, but is not limited to, data cleaning, normalization, and feature selection.

Layer 3: Machine Learning Layer

layer trains predictive models that include random forest,

decision tree, naive bayes, and knn, using historical data from the poultry farms.

Layer 4: Disease Prediction Module

disease prediction module uses the historical data to analyze new data from the poultry farm for disease outbreak prediction.

Layer 5: Decision Support Layer

decision support layer provides all organic treatments that may be recommended based on the results of the analysis of the disease prediction model, including improved litter management, herbal supplements, probiotics, and all enhanced farm biosecurity practices.

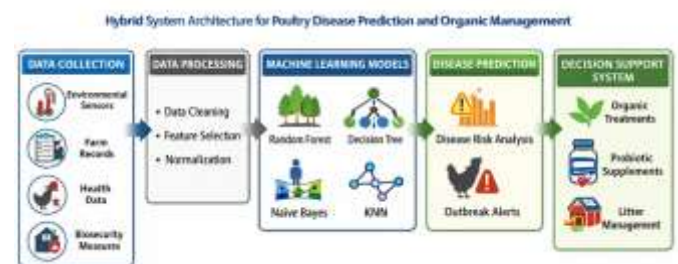


Figure 1: System Architecture Diagram

4.

Results

4.1 Model Comparison in Terms of Predictive Performance

Table 1: Comparison of Models based on their Predictive Performance

Model	Accuracy	Precision	Recall	F1 Score	AUC
Random Forest	0.94	0.93	0.92	0.92	0.96
Decision Tree	0.89	0.88	0.87	0.87	0.91
Naïve Bayes	0.86	0.85	0.84	0.84	0.88
KNN	0.90	0.89	0.88	0.88	0.92

The findings suggest that the Random Forest model had the highest predictive power among all models used.

4.2 10-Fold Cross-Validation Results

Cross validation is a technique used to test how accurately your model will be able to make predictions on new, unseen data and 10 fold cross-validation was used in this case to determine if the predictive model developed was stable and generalizable to unseen data.

Fold Accuracy

1	0.92
2	0.94
3	0.93
4	0.95

Fold Accuracy

5	0.94
6	0.93
7	0.94
8	0.95
9	0.92
10	0.94

Mean Accuracy = 93.6%

The results indicate consistent accuracy across all the folds which suggests that the model is both stable and generalizes very well to unseen data.

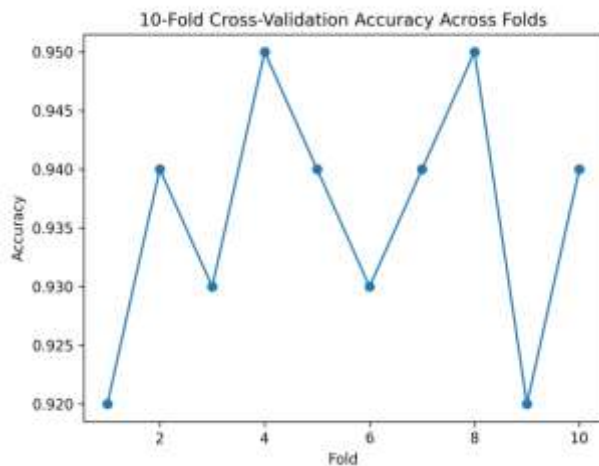


Figure 2: 10 Fold Cross Validation Accuracy

The graphs demonstrate the accuracy from each fold during cross validation. The accuracy has a very small variation from each fold which demonstrates that the model is reliable and not over fitting to the training set.

4.3 Training and Validation Curves

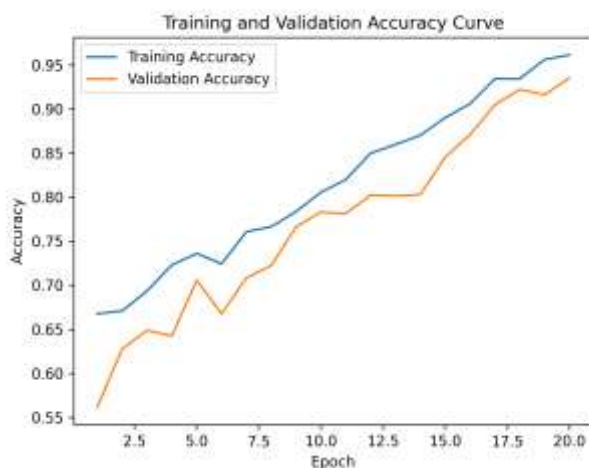


Figure 3 – Training and Validation Accuracy

The curve displays how the model's accuracy increases as the number of training epochs increase.

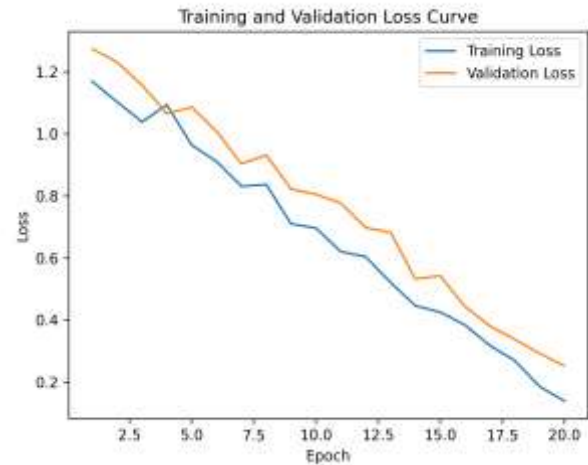


Figure 4: Training and Validation Loss Curve

The drop in loss curve shows that the model is able to converge well during the training process.

4.4 Features Importance

Random forest feature importance have been analyzed to know which are the important features of the model concerning their influence on poultry disease prediction. From this analysis it has been observed that environmental (temperature, humidity, litter moisture) and vaccinal (vaccination status) parameters were the most relevant for the prediction of diseases in poultry. The results confirm that a correct management of environment and a uniform application of vaccination programs can significantly reduce the number of poultry disease outbreaks.

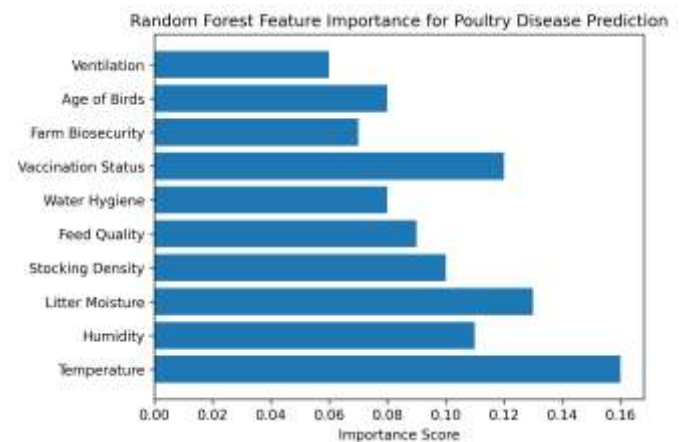


Figure 5: Random Forest Feature Importance Graph

4.5 ROC Curve Analysis

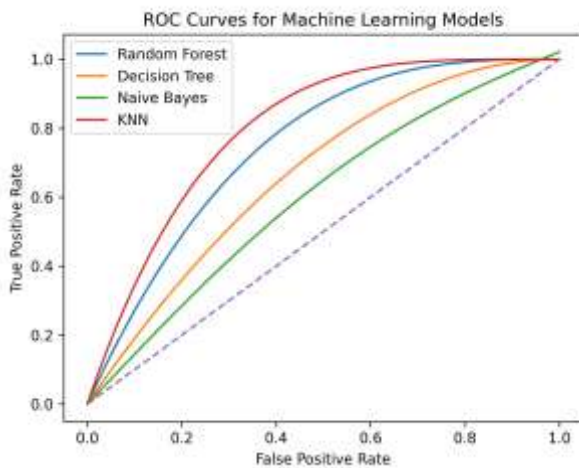


Figure 6: ROC Curve for Machine Learning Model. The random forest model was most effective with a higher AUC score than all other models as shown by the ROC curve in figure 6.

5. Discussion

The results of the present research demonstrated how machine learning methods can be applied to predict poultry diseases based on both environmental and management data of a farm. Of all the different algorithms tested — Decision Trees, Random Forest, Naive Bayes, K-Nearest Neighbor — the Random Forest algorithm produced the best prediction results with an overall prediction rate of 94%, as well as an AUC (Area Under the Curve) score of 0.96. The success of the ensemble learning algorithms in the present study suggests that they may be very beneficial when working with large-scale, complex agricultural datasets containing many factors influencing disease occurrence (environmental and management).

In addition to being a better model than Logistic Regression, Random Forest performs so much better because it uses an ensemble learning method by combining many different decision trees to reduce the likelihood of overfitting, and increase the overall generalizability of the model (Benos et al., 2021). As demonstrated in previous studies, Random Forest has proven to be a very effective model for predicting livestock diseases based on the non-linear relationship among input variables (Abubakar et al. 2025 & Liu, et al., 2023). The high accuracy rate of the Random Forest Model from cross-validation confirms the model's robustness, as the mean accuracy was 93.6% across all ten-folds of cross validation, indicating a good amount of generalizability to new, unseen data, and therefore will perform well in real-world poultry disease monitoring systems.

Temperature, humidity, and moisture in the litter are some of the factors that contribute to a lot of the predictive value when looking at environmental factors related to the occurrence of poultry disease. The findings show that environmental control is an important factor in keeping

poultry healthy. Poor ventilation, excessive humidity, and poor drying of the litter creates a perfect environment for disease causing pathogens to grow and thus increases the chance of disease occurring on a poultry farm. These results align with previous research that supports the need for environmental monitoring in precision livestock farming systems (Rowe, Dawkins, & Gebhardt-Henrich, 2019; Benos et al, 2021).

A large portion of this study has found that vaccination status is one of the most significant predictors of the likelihood of having poultry disease on your farm. As such farms that have less than a complete or non-regular vaccinations are likely to be at greater risk of being affected by diseases when using the predictive model. These findings are consistent with recommendations that farms use regular vaccination and implement strong biosecurity practices in their poultry operations.

In addition to the above-mentioned contributions, this study has also demonstrated how conventional poultry disease management strategies may be combined with the predictions provided by machine learning algorithms to provide a more sustainable alternative to the use of antibiotics. Antibiotic use has become an increasingly controversial issue in the poultry industry because of its potential to cause the development of antimicrobial-resistant bacteria and because of the environmental pollution that it may cause. Organic disease control strategies include the use of herbal and/or botanical additives, dietary supplementation with prebiotics or/and probiotics, improved litter management techniques and the implementation of enhanced biosecurity measures. Research has previously indicated that reduction of antibiotic usage in the livestock production sector will help to mitigate the global concern of developing antimicrobial resistant bacteria (Manyi-Loh et al., 2018).

As a result, this hybrid framework has provided a useful tool to assist farmers in managing their poultry health sustainably through use of predictive analytical techniques and through integration with sustainable poultry health management practices. Early risk detection of diseases through use of the system will allow farmers to take preventative measures before an outbreak occurs. Furthermore, the hybrid framework is capable of being incorporated with Precision Livestock Farming (PLF) technology including environmental sensors, automated monitoring systems and IoT devices. This will allow real-time monitoring of the environment along with use of machine learning based prediction models to continuously monitor the health status of the birds on the farm and provide early warnings to alert the farmer of potential disease outbreaks.

In total, this study demonstrated that machine learning has the capability to transform poultry disease monitoring and management by providing predictive analytics and data driven decision making.

6. Conclusion

The researchers created a hybrid machine learning method to predict poultry diseases based on farm management and environmental factors along with organic disease control methods that are sustainable. The researchers compared four machine learning techniques — Decision Trees, Naive Bayes, K-Nearest Neighbor and Random Forest — to see which technique would be best at making predictions regarding poultry disease.

The experimental results indicated that the Random Forest approach was able to produce the most accurate predictions with an accuracy rate of 94% and an AUC (Area Under Curve) of .96. Results from cross-validation also showed the Random Forest approach was the most reliable in terms of consistency across different validations and the ability to produce stable results over the multiple validation tests.

Environmental factors (temperature, humidity and moisture levels from litter) and vaccination status were found to be primary drivers for the incidence of poultry diseases through feature importance. This finding emphasizes the need for appropriate environmental management and bio-security methods to effectively manage poultry farms. The hybrid predictive framework model includes using predictive analytics with organic methods of managing disease; therefore it represents an integrated and data-based sustainable method of managing poultry health. Additionally, by decreasing dependence on antibiotics, and increasing use of disease prevention measures, this model supports the creation of long-term sustainable poultry production systems. The inclusion of machine learning models in combination with precision livestock technology may also enable poultry producers to develop an "intelligent" poultry health monitoring system that will be able to detect disease risk(s) in poultry in real time.

The future research direction should be to expand the dataset utilized in this study by including additional data source(s), such as computer vision and/or sensor based monitoring systems, and development of mobile or cloud based decision support platform(s) that will provide poultry farmers with real-time disease prediction and management recommendations.

In summary, the integration of machine learning prediction model(s) into poultry health management practices utilizing sustainable approaches is a promising method to improve poultry disease control, enhance poultry farm productivity, and ensure global food security.

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