

Development of an AI-Driven Mobile Application for Poultry Disease Diagnosis and Decision Support Using a Pre-Trained Transformer-Based Model

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Abstract

Poultry farming remains a major contributor to every nation's economy, yet it is faced with many challenges, especially during disease outbreaks. In developing nations, the majority of poultry farmers lack formal knowledge in the field and access to extension agents. This article proposes the development of an AI-driven mobile application for poultry disease diagnosis and decision support that leverages a pre-trained transformer model. A dual architectural framework that integrates a Convolutional Neural Network-based image classifier and a transformer-based model was used for image-based disease detection and expert-level diagnosis and treatment recommendations, respectively. The application was developed using object-oriented analysis and design methodology. The results of the framework show that the best image-based classifier achieved 84.53% accuracy in classifying the listed poultry diseases. The transformer models also presented average precision accuracy (PA) of 95%, professional rating (PR) of 95%, a coherence rating (CR) of 97%, and a task success rate (TSR) of 96% based on the aggregation of independent assessments from 3 domain experts. These results prove that a mobile application can be engineered to democratize the possibilities associated with engaging machine learning (ML) in poultry farming since existing AI tools were not designed for illiterate farmers. Nevertheless, human veterinary professionals remain indispensable, especially in context-specific cases where clinical examination and consideration of birds' health history are required to complement AI-driven insights.

Keywords: AI in Agriculture, Poultry Disease Detection, AI Decision Support, Personal Farming Assistant, Transformer Models.

Introduction

Poultry farming contributes to the world global food system. It involves the raising of birds for the use of man either at commercial or subsistent level. In developing countries, it is one of the branches of animal husbandry that is practiced by majority of farmers including those

without formal education in the domain of agriculture. This set of farmers (those with no formal education in poultry farming domain) fit to be categorized as novice farmers do face some serious challenges especially in the event of disease outbreak due to their limited access to veterinary and technical support. Although many approaches for combating disease outbreaks have been proffered, researches show that artificial intelligence (AI) has proven to offer transformative solutions, particularly through machine learning (ML) models (Ahmed & Kannan, 2021; Cakic et al., 2023; Tsiouris et al., 2024; Zhuang & Zhang, 2019).

In addition to illiteracy as a problem with the novice farming population is their inadequate decision-making capability in poultry farming, which is also grossly caused by their bankruptcy of knowledge in the domain. This knowledge bankruptcy has led to disease outbreaks escalating without control, resulting in significant losses. In addition, their unprofessional knowledge of feed planning, environmental control, and stock health monitoring further compounds these inefficiencies (Ibrahim et al., 2016; Nassar & Abbas, 2025).

These problems have been proven to be largely solved by the use of artificial intelligent solutions. However, a systematic review conducted by (Erike *et al.*, 2025) shows that existing AI-solutions that has been proffered in the poultry domain were not engineered for illiterate farmers.

Research Question

RQ1. Can AI-Driven solution(s) be engineered to support novice poultry farmers in disease detection and management?"

Research Objectives

The objectives of the research are to:

- i. Integrate a dual-architecture framework that integrates CNN for poultry disease detection and transformer-based model for personalized diagnosis for treatment recommendations.
- ii. Evaluate the performance of different CNN architectures in classifying poultry diseases from fecal images.
- iii. To assess the effectiveness of the transformer-based model in generating accurate, coherent and professional disease diagnosis and treatment recommendations for novice poultry farmers.

Literature Review

Poultry Disease Detection using AI

Reviewed literatures reveal scholarly works that have applied machine learning in areas like poultry disease detection, monitoring, feeding optimization, tracking, and so on. Several approaches have been employed by researchers in the area of poultry disease detection, such as vocalization-based disease detection (Banakar et al., 2016), faecal-based

classification (G. Li & Ramirez, 2023), avian influenza classifiers (Tsiouris et al., 2024), behaviour classifier using LightGBM (Mohialdin et al., 2023), CNN for poultry health classification (Osagie & Cyril-Musa, 2024), and Salmonella disease prediction using ensemble learning techniques (Pillai et al., 2022). Further on disease surveillance and detection, (Cakic et al., 2023) developed an edge-AI solution using Faster R-CNN, while (Sadeghi et al., 2023) combined thermal imaging and ML for detecting poultry diseases like Newcastle and Avian Influenza. Researchers have also leveraged deep learning to detect early signs of poultry diseases (Yajie et al., 2023). Likewise, (Alberts et al., 2024) applied Random Forest and Gradient Boosting to classify hosts of influenza H3Nx viruses. U-Net and YOLOv5 have been used to classify faecal samples of birds for early health prediction (Nakrosis et al., 2023), and (Azadeh et al., 2014) combined ANN with system dynamics for broiler industry optimization.

AI for Poultry Monitoring and Tracking

Further reviews show that different variants of YOLO have been employed for monitoring and tracking in the poultry domain. Chicken behaviours were successfully monitored by (Merenda et al., 2024), using an integration of YOLOv5 and Gradient Boosting with significant results. Still with YOLOv5, (G. Li & Chai, 2023) was able to measure spatial behaviours in laying hens. (Yang et al., 2024) extended the tracking capabilities of ML to track hen behaviour and health in cage-free environments using YOLOv5, YOLOv8, and DeepSORT.

In the area of monitoring and tracking, the different variants of YOLO have been employed to monitor movements and behaviours in poultry farming. Individual chicken behaviours were monitored by (Merenda et al., 2024), integrating YOLOv5 and Gradient Boosting. In yet another study, (G. Li & Chai, 2023) applied YOLOv5m to measure spatial behaviour in laying hens, and (Yang et al., 2024) utilized YOLOv5, YOLOv8, and DeepSORT to track hen behaviour and health in cage-free environments. (Depuru, 2024; Neethirajan, 2022b) introduced "ChickTrack," a YOLOv5-based system for tracking chicken behaviour and thus automated the system with significant result. Advanced computer vision models like those used by (Subedi et al., 2023) and (Cui et al., 2023) have also enabled real-time floor egg tracking and broiler health status recognition, respectively. Meanwhile, (Campbell et al., 2024) employed CNN and GMM for activity monitoring in commercial broilers.

AI for Feeding and Optimization

In feeding and nutrition optimization, (You et al., 2020) applied Random Forest classifiers to predict daily oviposition events in broiler breeders with 85% accuracy. In addition, (Chen et al., 2023) employed Support Vector Regression and ANN to predict breast muscle and abdominal fat in broilers, while (Z. Li et al., 2023) implemented various models such as MLR, LASSO, and SVM to estimate breast muscle weight via ultrasound. (Bumanis et al., 2022) designed a smart management platform using XGBoost for egg production forecasting, while (Neethirajan, 2022a) used ANN to predict oviposition probabilities with 94.1% AUC.

Other studies like (Yu et al., 2024), used a cyclic consistent migration neural network for enhanced image detection in caged chickens, and Liu et al., (2025), simply evaluated ML methods for genomic predictions in yellow-feathered broilers. Combined AI and IoT in an edge-computing have also been effectively used in poultry monitoring system, while deep learning methods have also been employed for clinical symptom monitoring (Chen et al., 2023).

Research Gaps

Despite a rich landscape of research in the poultry farming domain, there are still some gaps. Most of the studies focus narrowly on disease detection or production optimization, but lack integration into a user-centred, personalized assistant model. Secondly, a few tools provide real-time, day-to-day guidance for novice farmers or combine multiple AI functionalities into a holistic solution. Moreover, existing systems were often developed for researchers or commercial operators, not beginner-level farmers who need simplified interfaces and localized support.

This research addresses these gaps by developing an AI-driven mobile application for poultry disease diagnosis and decision support using pre-trained transformer-based model, tailored specifically for novice farmers.

Methodology

Proposed Architecture

The research follows a dual architecture that combines deep learning technique and transformer-based architecture. The high-level system architecture is represented in figure 1. The architecture comprises of different modules. At first, we have the vision layer, implemented using a smartphone's camera. With this, the user (farmer) captures an image of the poultry feces. The image serves as input to the system which triggers disease diagnosis. The captured image is passed to an ML model—typically a Convolutional Neural Network (CNN) trained to detect diseases for visual features. This model outputs predictions, e.g., "Detected: Coccidiosis with 92% confidence", which reflects class labels, confidence scores, severity indicators, and so on. It uses an API Connection to pass the structured data to the Transformer Layer's Output Encoder which encodes, and structures the prediction from the ML model into a format that is understandable by the downstream system.

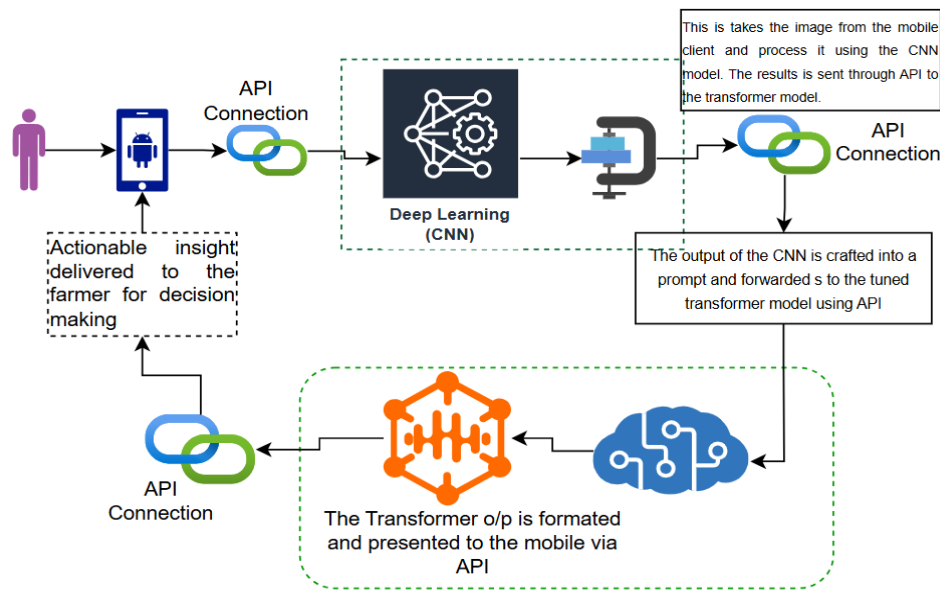


Figure 1: The high-level system architecture of the proposed application

The transformer layer accepts structured diagnosis and other contextual data (e.g., bird age, type) and outputs a personalized, human-readable response like: *"Your broiler appears to have symptoms of coccidiosis. Administer 'drug type' in water for 3 days. Isolate the sick birds and sanitize the coop."* In this post-processing stage, the transformer's natural language response is refined, formatted, and checked for readability, language preference, or message type (e.g., text, push notification), and may also include safety flags (e.g., urgency). At the application user interface, the farmer receives the final recommendation from the transformer on their mobile applications through an API connection. Data to be displayed include: diagnosis, recommended treatment, and suggested actions. The user interface allows feedback loops.

Data Collection

A total of twelve thousand (12000) already classified poultry fecal images were sourced from www.kaggle.com. The classes are as follows: healthy, salmonella, coccidiosis, and new castle disease. The secondary data sourced from Kaggle were kept for both training and testing purposes while the primary data sourced locally were kept for contextual validation purposes. No further processing was needed except for the validation of labelling correctness.

Model Development

The secondary dataset was split in the ratio of 80:20. While the 80% was used for training purposes, 20% was reserved for testing purposes. The following variants of CNN architectures: (EfficientNet-Bo, Simple CNN, ResNet-18, and MobileNetV2) were trained using the dataset. This is basically to know the one that performs better at classifying the

fecal images under the same conditions. The training phase employed the following hyper-parameters values stated in table 1 to ensure optimal model performance:

Table 1: Training parameters for the CNN model development

Training Parameters	Parameter values
Learning rate	0.0001
Batch size	32
Number of epochs	10
Optimizer	Adam
Loss function	Categorical Cross-Entropy
Activation functions	ReLU (hidden layers), Softmax (output layer)
Input image size	224 x 224 by 3 channels
Dropout rate	0.5 (to prevent overfitting)
Kernel size	3x3
Pooling	MaxPooling with 2x2 window

The CNN architecture consisted of multiple layers including convolutional layers, activation layers, pooling layers, flattening layers, and fully connected (dense) layers. Mathematically, the output of a convolutional layer at position (i, j) in the feature map is given in equation (1)

$$O_{i,j}^{(l)} = f \left(\sum_{m=1}^M \sum_{p=1}^k \sum_{q=1}^k W_{p,q}^{(m)} \cdot X_{i+p,j+q}^{(m)} + b^{(l)} \right) \quad (1)$$

Where: $O_{i,j}^{(l)}$ is the output layer; f is the activation function (ReLU), W represents the filter weights, X is the input from the previous layer, $b^{(l)}$ is the bias, $K \times k$ is the filter size, and M is the number of input channels. The final classification is obtained by using a Softmax function defined by equation (2).

$$\text{Softmax}(Z_i) = \frac{e^{Z_i}}{\sum_{j=1}^C e^{Z_j}} \quad (2)$$

Where: Z_i is the input to the output layer for class i , and C is the total number of classes. The model was fine-tuned to maximize classification accuracy and generalization performance on unseen fecal image data, and to prevent over fitting.

1.1 ML Output Encoding versus The Pre-Trained Transformer-based Large Language Model

The rule-based prompt mapping approach was employed to translate the output of the CNN model into prompts that are suitable for dynamically querying the pre-trained transformer-based large language model. The choice of the rule-based approach is to be able to track model input stability. As shown in figure 2, this method uses conditional logic, such as if-else statements or decision trees, to determine both the relevant content and the appropriate format of each prompt.

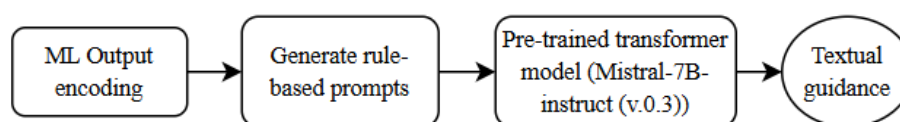


Figure 2: Rule-based prompt matching architecture for pre-trained transformer models

The Mistral-7B-instruct (v.o.3) model was chosen as the transformer model to interpret classification outputs, generate explanations and perform reasoning on labels. The choice of this pre-trained transformer model instead of other larger large language models (LLMs) was because it is lightweight, supports quantization and local deployment, and it runs efficiently on modest hardware. The instruct v0.3 version is a fine-tuned version of the base pre-trained model optimized for following human instructions. Instructions to the model is passed through context engineering. Contextual instructions were designed to minimize model hallucination, thereby ensuring that the generated outputs approximate those of a human expert. Hence, the model only replies to what it knows following a specified format, and ignores every other query outside of its specified field. Meanwhile, the specified field (in this case, 'poultry farming expert – doctor or scientist') is incorporated into the context instruction. The Transformer interprets the context and generates personalized textual guidance, including treatment steps, preventive measures, and biosecurity tips. It was placed to operate based on the instruction passed through the context as follows:

"You are a veterinary professional assistant specializing in poultry health. Based on the detected disease from a CNN model, you will provide recommended drug prescriptions, dosages, and administration guidelines in line with veterinary standards. If there is need for a specific administration method for tough scenarios, also state it. Always include drug alternatives, preventive measures, and a caution that farmers should consult a vet before final action".

To optimize the transformer model performance, the model-side parameters which include: the model size, learning rate, batch size, dropout rate weight decay, sequence length, and the inference-time parameters which includes the temperature, top-k sampling, top-p (nucleus sampling), and the beam search width were tuned with values as shown in table 2.

Table 2: Mistral-7B-instruct (v.o.3) parameter tuning values

Inference-time parameter	value	Operation
Temperature	0.20	Helps to control randomness in output generation (0 = deterministic, 1 = creative)
Top-k sampling	90	Limits token choice to top k most likely
Top-p (nucleus sampling)	0.20	Chooses tokens until probability mass p is reached
Beam search width	4	This helps to find the best sequence instead of performing greedy decoding

Evaluation Framework and Metrics

The study evaluates how effectively the Mistral-7B-Instruct (vo.3) model provides professional-like textual guidance to users through the mobile application interface by using a human-in-the-loop evaluation approach. three experts were independently selected for this task. The aim was to evaluate the responses of the model in different scenarios given specific conditions. The evaluation metrics in table 3 was provided to guide their individual assessments.

Table 3: Mistral-7B-Instruct (vo.3) model output evaluation metrics

Metric	Description	Measurement Scale
<i>Accuracy Score</i>	Measures correctness of responses against domain-specific reference standards.	Percentage (%) of correct responses
<i>Task Success Rate</i>	Measures the proportion of tasks successfully completed according to predefined benchmarks.	Percentage (%) of successful tasks
<i>Coherence Rating</i>	Assesses logical flow, clarity, and consistency of responses.	10-point Likert scale (1 = poor, 10 = excellent)
<i>Professionalism Rating</i>	Evaluates tone, structure, and adherence to expected professional standards.	10-point Likert scale (1 = poor, 10 = excellent)
<i>Validation accuracy</i>	Percentage of correct predictions on validation data	$\frac{\text{Number of correct predictions}}{\text{Number of total predictions}}$ Ranges from 0 – 100%
<i>Precision</i>	This metric measures the number of positive predictions that are actually correct	$\frac{TP}{TP+FP}$ Ranges from 0 -1
<i>Recall</i>	Measure the percentage of actual positive correctly identified	$\frac{TP}{TP+FN}$ Ranges from 0 -1
<i>F1 score</i>	Measures the harmonic mean of the precision and recall	$\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \times 2$
<i>Generalization gap</i>	Measures the difference between training and validation performance	<i>Training accuracy – Validation accuracy</i>
<i>Generalization error</i>	Measures the error rate on unseen data	Ratio scale $1 - \text{Test accuracy}$

Results and Discussions

Deep Learning Model Results

The data was trained using the following four CNN architectures - EfficientNet-Bo, Simple CNN, ResNet-18 and MobileNetV2. The following metrics were used to evaluate the performance of the models: Validation accuracy, Precision, Recall, F1 Score, Generalization gap and Generalization error. The results are presented in table 4. Figure 3 shows the

visualization of the different architectures both for the training and validation and accuracy and training and validation loss.

Table 4: Models' performance evaluation summary table

Model	Val. Accuracy	Precision	Recall	F1 Score	Gen. Gap	Gen. Error
EfficientNet-Bo	84.53%	85.34%	85.86%	84.90%	1.27%	1.51%
Simple CNN	76.80%	77.10%	76.40%	76.75%	1.70%	2.10%
ResNet-18	80.90%	81.10%	80.40%	80.75%	1.40%	3.00%
MobileNetV2	78.90%	79.20%	78.40%	78.80%	1.70%	1.50%

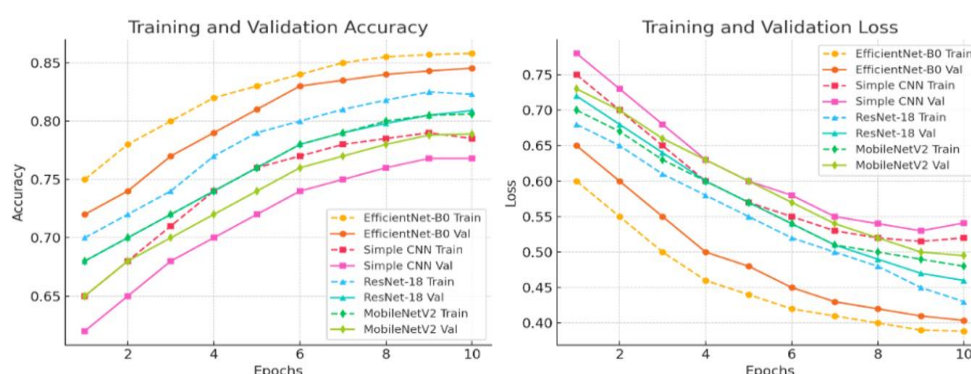


Figure 3: A combined graph of the individual models' performances based on validation accuracy and validation loss.

The AI model evaluation demonstrates that the EfficientNet-Bo outperformed other CNN architectures in nearly all performance metrics. Having a validation accuracy of 84.53%, it exceeded the baseline Simple CNN (76.80%), ResNet-18 (80.90%), and MobileNetV2 (78.90%). EfficientNet-Bo also was leading in precision (85.34%) and recall (85.86%), hence, producing the highest F1 score of 84.90%, which reflects a well-balanced classification performance. Its generalization gap (1.27%) and generalization error (1.51%) were among the lowest. This shows that it has good adaptability to new data. In comparison, the Simple CNN had a generalization gap of 1.70% and a higher error of 2.10%, while ResNet-18 and MobileNetV2 showed moderate gaps and errors. All models were trained over 10 epochs, but EfficientNet-Bo's training and validation losses (0.3886 and 0.4037) confirmed that it has stable convergence. Table 4 summarizes key metrics for a clearer comparison.

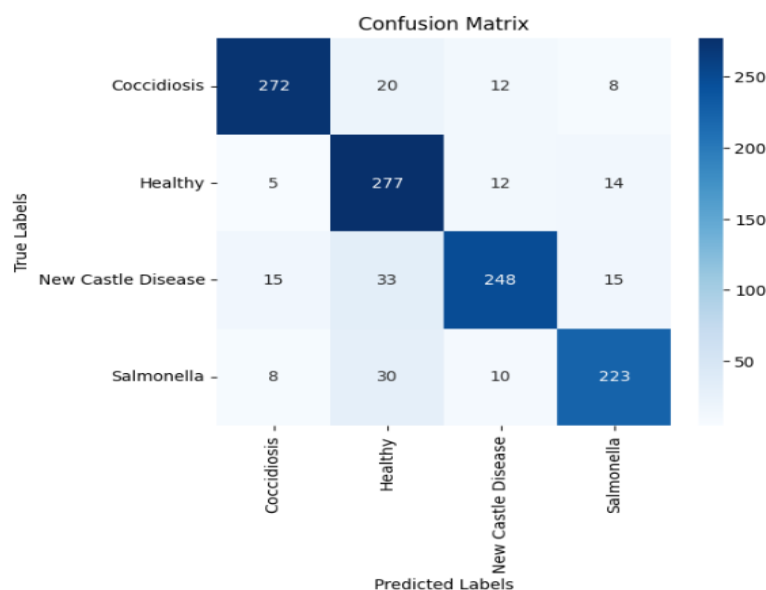


Figure 4: The confusion matrix showing the different diseases classifications

The confusion matrix shown in figure 4 provides a detailed breakdown of the model's classification performance by showing the number of correct and incorrect predictions made for each of the disease classes (Coccidiosis, New Castle Disease, and Salmonella). The heat map clearly shows how well the model distinguishes between different poultry diseases. The strong diagonal in the matrix indicates high prediction accuracy, where predicted classes match actual classes, while the off-diagonal values highlight confusion between specific disease pairs, showing that the model had a bit of struggle. Hence, based on the precision (85.34%) and recall (85.86%) reported, the confusion matrix shows minimal misclassifications which affirms the model's strong discriminative ability across the different classes of diseases under consideration.

The Transformer-Based Model Result

The efficiency of the Mistral-7B-Instruct (v0.3) model was tested using 120 test inputs samples from the CNN model, 40 test cases for each of the following diseases: Coccidiosis, Salmonella and New Castle disease. This number was selected to capture responses across varying confidence levels that could result from factors such as disease severity, image angle, and lighting conditions. Also, for proper estimation of mean ratings and confidence intervals, and to improve statistical confidence in the estimation of accuracy and success rate. The samples were generated by adjusting the confidence level from 60% to 99%. All other parameters in the model tuning were kept constant. The average results are as presented in table 5.

Table 5: Mistral-7B-Instruct (vo.3) model evaluation scores from human professionals

Evaluation Method	Accuracy Score (%)	Task Success Rate (%)	Coherence Rating (Mean)	Professionalism Rating (Mean)	Professional Comment
<i>Coccidiosis</i>	100	100	100	99	Excellent clinical accuracy
<i>Salmonella</i>	92	100	96	90	Good, but treatment recommendations are not optimal per resistance trends
<i>New Castle disease</i>	94	88	100	95	Very good, but supportive therapy emphasis should be clearer
<i>Average</i>	95	96	97	95	

The results in table 5 show an average accuracy of 95% and a professional rating of 95% which indicates the ability of the system to confidently stand in place of a human professional. The average coherence rating of 97% is indicative of the fact that the model behaves consistently to professional extent over certain diseases detected. The average task success rate of 96% would have been due to data exchanges made during API calls. These could have been caused by data signal strength and availability of communication gateways as at the time of communication. This success rate is however acceptable based on the fact that the system is not designed to be a hard-real time system. Despite the performance of the model, human professionals are not supposed to be left out of treatment especially where the model outputs did not take cognizance of the health history of the birds especially as it concerns the disease resistant levels.

Conclusion

Although significant breakthroughs have been recorded experimentally in leveraging the capabilities of AI and ML in advancing poultry farming, analysis of existing literatures show that existing implementations seem not to favour the illiterate farming population. Hence, the study demonstrates the possibility of engineering an AI-driven personalized assistant designed for the use of the illiterate farming population. The research presented a dual-architecture system that integrates a CNN-based disease classifier for disease image detection and classification, and a transformer-driven model (Mistral-7B-Instruct (vo.3) model) for natural language-based assistance that mimics the role of a veterinary professional. The results from CNN classifier engine – precision (85.34%) and recall (85.86%), and that from the transformer model (accuracy: 95%, success rates: 96%, coherence rating: 97% and professional rating: 95%) as ported into a mobile application using APIs represents a proof of concept.

We recommend that future work could focus on field validation of the application with locally-collected dataset. Secondly, the research focused on only few disease classes. Steps could be taken to expand the disease classes. Finally, further research could consider engineering the application to accommodate network variabilities that may affect the operations of the transformer model.

Conflict of Interests: Authors declare that they have no conflict of interests

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