Smart Mobile App for Detecting Coccidiosis in Droppings Using Deep Learning*

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Abstract

Avian coccidiosis is a parasitic disease that causes significant economic losses in poultry farms. This study proposes a preventive solution based on the analysis of broiler droppings to detect early signs of the disease, particularly yellowish droppings. A mobile app allows poultry farmers to capture images directly in the field to assess the health status of their flocks. Four deep convolutional neural network (CNN) models using transfer learning were developed and evaluated: ResNet50, MobileNetV2, VGG16, and Xception. Among them, MobileNetV2 achieved the best performance with an accuracy of 99.2 %, a recall of 99.5%, a precision of 98.9 %, and an F1-score of 99.2 %. The dataset used comprises 4,251 images of avian droppings, divided into 2,103 images in the "coccidiosis" class and 2,148 images in the "healthy" class, including 91 collected at The Farmer King farm in Pahou, in southern Benin. After data cleaning and preprocessing, the final dataset used was reduced from 2,103 to 1,970 images for the "coccidiosis" class and from 2,148 to 2,145 images for the "healthy" class, for a final total of 4,115 images. These results demonstrate the proposed system's ability to effectively detect early signs of coccidiosis in poultry droppings. Integrating the model into a mobile app thus provides poultry farmers with a practical decision-making tool, enabling rapid intervention and potentially reducing economic losses associated with the disease.

Keywords

Artificial Intelligence, Deep Learning, Coccidiosis, Poultry Farming

1. Introduction

Coccidiosis in chickens is the most widespread protozoan disease, which severely impacts production and causes significant economic losses worldwide. To successfully control coccidiosis in chickens, it is necessary to implement proper management [1]. It is therefore important to have tools available that allow for rapid diagnosis of the health status of poultry.

In the face of rapid population growth, the demand for protein particularly from poultry continues to rise in order to meet the population's ever-increasing nutritional needs [2]. However, this goal cannot be achieved without effective control of avian diseases, which pose a major challenge to poultry health and productivity. Among these diseases are coccidiosis, salmonellosis, Newcastle disease, and avian influenza, which directly impact the profitability of poultry farms.

Traditional methods for detecting coccidiosis often require microscopic analysis or specialized veterinary examinations. These approaches have several limitations: high cost, slow diagnosis, and limited accessibility in rural farms. However, chickens cannot be raised intensively without the risk of coccidiosis, a condition that can be considered a disease of intensive farming systems [1]. According to [3], the first symptom frequently observed is yellow diarrhea, which gradually changes to a red or caramel color, indicating the presence of blood and dehydration. Sometimes, farmers detect this disease at an already advanced stage. It is therefore necessary to offer a smart, fast, and accessible solution that works directly on a smartphone to help farmers detect the disease early in their flock and take immediate action.

Predictive models are used in veterinary epidemiology to predict outbreaks and guide intervention strategies. AI applications are also promising in this field. AI models can assess the risk of outbreaks by

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analyzing data on animal movements, weather patterns, and past outbreaks. This will help veterinary professionals and authorities take preventive measures [4, 5].

Our project is part of this initiative. It involves developing an AI model,trained using images of broiler chicken droppings, which is then integrated into a user-friendly mobile app designed to help poultry farmers monitor the health of their poultry.

2. Related Work

Several studies have explored the use of deep learning for the diagnosis of avian diseases based on images. In particular, convolutional neural networks (CNNs) have demonstrated strong performance in the classification of medical and agricultural images. KUKU is a mobile application developed to automatically detect several avian diseases, including coccidiosis, salmonellosis, and Newcastle disease [6]. The authors used the YOLOv3 model for object detection as well as various image classification models. The system achieved an overall accuracy of 98.7%.

In 2024, a study presented at the Conference on Image Processing and Capsule Networks (ICIPCN) [7] proposed an approach based on the VGGNet architecture to detect coccidiosis using microscopic images of fecal samples. The results demonstrate the effectiveness of deep learning for the automated identification of infected samples. However, this approach still relies on microscopic analysis requiring laboratory equipment.

Other studies have used images of avian droppings to classify various diseases such as coccidiosis, salmonellosis, and Newcastle disease. Several CNN architectures, including VGG16, InceptionV3, MobileNetV2, and Xception, were evaluated. After model tuning, MobileNetV2 and Xception achieved accuracies of 98.02 % and 98.24 %, respectively [5]. Unlike existing approaches, which often rely on laboratory analyses or microscopic images, our work proposes a mobile solution based on the direct analysis of broiler chicken droppings collected in the field. This approach aims to provide farmers with early, rapid, and accessible detection of coccidiosis [5].

3. Background

3.1. Deep Learning

Deep learning is a branch of artificial intelligence based on the use of multilayer artificial neural networks capable of automatically learning complex representations from data. This approach is now widely used in several fields, such as computer vision, natural language processing, and medical diagnosis [8].

Among the most widely used architectures in computer vision are convolutional neural networks (CNNs). CNNs are particularly well-suited for image analysis thanks to their convolution, pooling, and classification layers, which enable the automatic extraction of important features from an image while reducing data complexity. In the field of animal health, CNNs are increasingly being used for the automatic detection of diseases based on medical or biological images. Several pre-trained architectures, such as ResNet50, VGG16, MobileNetV2, and Xception, have demonstrated excellent performance thanks to transfer learning.

3.2. Coccidiose Aviaire

Avian coccidiosis is a parasitic disease caused by protozoa of the genus *Eimeria*. It is one of the most common and costly diseases in poultry farming, particularly among broiler chickens [9]. This disease primarily affects the poultry's intestines and causes several symptoms, such as diarrhea, blood in the feces, weight loss, stunted growth, and reduced production performance [10] [11]. In severe cases, it can lead to significant mortality within the flock.

Traditional diagnosis is generally based on clinical observation, microscopic analysis, or laboratory tests. However, these methods often require time, specialized equipment, and the involvement of veterinary experts, which limits their accessibility to small-scale farmers [12]. Finally, according to [3], the first symptom frequently observed is yellow diarrhea, which gradually turns red or caramel-colored, indicating the presence of blood and dehydration.

Coccidiosis is transmitted primarily through the feces of infected birds, which contaminate the soil and bedding, especially when it is damp. It can also spread via contaminated farm equipment, clothing, bags, rodents, or disease-carrying insects. As noted by [13], transmission occurs via the fecal-oral route: oocysts shed by infected poultry spore in the animal's bedding when conditions are favorable, and are then ingested by other individuals.

The analysis of bird droppings is therefore a promising approach for the early detection of the disease. Recent advances in deep learning now make it possible to automate this detection using images captured directly in the field with smartphones.

4. Methods and Data Source

4.1. Study Data

The data used in this study consist of images of poultry droppings, representing two classes: the "coccidiosis" class and the "healthy" class. These images were obtained both from online collections, notably on the Zenodo platform, and from data collected in the field at poultry farms.

A cleaning and preprocessing process was applied to eliminate noisy or unusable images. After processing, the final dataset consists of 4,115 images, divided into 1,970 images for the "coccidiosis" class and 2,145 images for the "healthy" class. Data annotation was performed with the assistance of domain experts to ensure the reliability of the labels assigned to each image. The dataset was then divided into training (60 %), validation (10 %), and test (30 %) sets.

4.2. Study Design

The proposed system takes a deep learning-based approach and consists of four main steps:

- **Image acquisition** : captures images of droppings via smartphone or online sources.
- **Data preprocessing**: image resizing, normalization, and augmentation.
- **Model training**: using pre-trained CNN models with the transfer learning method.
- **Deployment**: Integration of the model into a mobile application to enable real-time detection.

4.3. Study Methods

The images were resized to a uniform resolution of 224 × 224 pixels to match the inputs of the CNN models, followed by normalization of the pixel values to the range [0, 1] to improve training stability.

In this study, four pre-trained convolutional neural network architectures were evaluated: ResNet50, VGG16, MobileNetV2, and Xception. These models were initialized with weights pre-trained on ImageNet, using a *transfer learning* approach. To adapt these architectures to our binary classification task (presence or absence of coccidiosis in feces), the deep convolutional layers were frozen (`base_model.trainable = False`) to preserve the learned general representations. A custom classifier was then added to the output of each model, consisting of a `GlobalAveragePooling2D` layer for dimensionality reduction, a dense `Dense(256, relu)` for learning specific representations, a `Dropout(0.5)` layer to limit overfitting, and finally a `Dense(1, sigmoid)` output layer suitable for binary classification.

Training was performed using the Adam optimizer (with a learning rate of 10^{-4}), known for its stability, and the binary cross-entropy loss function, which is suitable for two-class classification problems. An early stopping mechanism was applied to halt training as soon as signs of overfitting appeared. The models were trained over 15 epochs with a batch size of 16 images per batch. Model performance was evaluated using complementary metrics: accuracy, recall, precision, and F1 score, enabling a rigorous evaluation focused on good generalization to the test data.

5. Implementation

5.1. Mobile Application

The mobile app was developed for the Android platform to enable farmers to use it directly in the field. It was built using Flutter and Android Studio, offering a simple, fast interface designed for non-technical users. The app allows users to either capture an image of droppings in real time using their smartphone's camera or import an existing image from their gallery. The image is then sent to the system for analysis.

5.2. Backend and Model Deployment

The system is based on a backend developed using Django Rest Framework (DRF), which exposes prediction capabilities via a REST API. The trained MobileNetV2 deep learning model was saved in `.h5` format, including the architecture, weights, and training configuration. This model is then loaded into the backend using the `tf.keras.models.load_model()` function.

The backend plays a central role in processing requests. It receives the images sent by the mobile app, performs the necessary preprocessing operations (resizing and normalization), and then passes the data to the model to make the prediction. The classification result is then sent back to the app as a JSON (JavaScript Object Notation) response, including the predicted class (coccidiosis or healthy) and the associated confidence score.

5.3. Prediction Pipeline

The system's overall pipeline follows these steps:

- Capture the image using the developed mobile application;
- Send the image to the backend via a REST API;
- Preprocess the image on the server side;
- Make a prediction using the MobileNetV2 model;
- Return the result to the mobile app.

The entire system is designed to be lightweight, fast, and suitable for use in rural areas, enabling early detection of coccidiosis directly in the field.

6. Results

Table 2 presents a comparison of the performance of the four CNN architectures evaluated. MobileNetV2 achieves the best performance with an F1 score of 99.2%. Figure 1 shows the learning curve for the MobileNetV2 model, illustrating the evolution of accuracy, loss, precision, and recall.

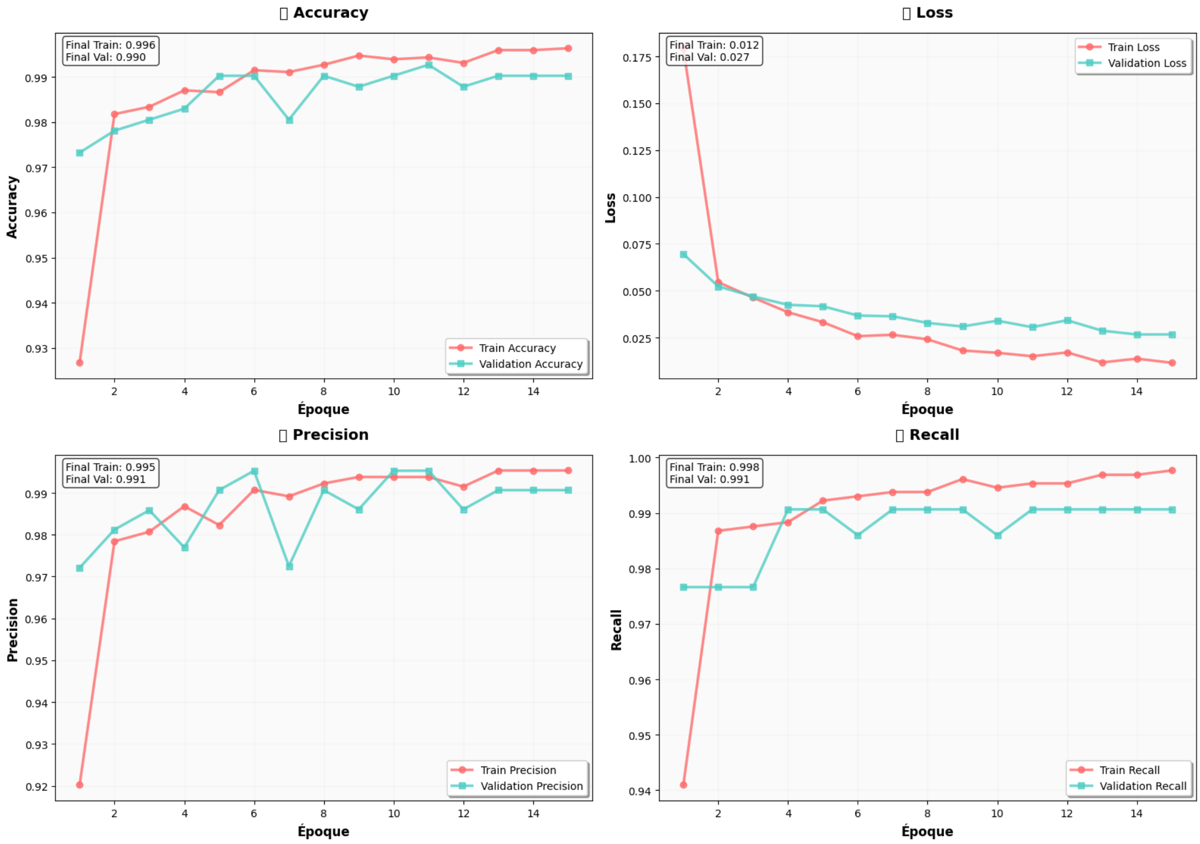

Figure 1: MobileNetV2 Learning Curve

The results show satisfactory accuracy in image classification. The model demonstrated good generalization ability on the test data.

Accuracy

The accuracy curve shows very rapid improvement starting from the first few epochs. The final training accuracy reaches 0.996, while the final validation accuracy reaches 0.990.

- A very marked improvement is observed between epochs 1 and 2.
- Performance remains high and stable throughout training.
- The difference between training and validation accuracies (≈ 0.006) remains small and acceptable.
- The stabilization observed after epoch 8 indicates rapid and effective convergence of the model.

Loss

The loss curve decreases sharply at the beginning of training and then gradually stabilizes. The final training loss is 0.012, while the final validation loss is 0.027.

- The initial sharp decrease reflects very rapid learning by the model.
- The gradual reduction in loss confirms effective parameter optimization.
- The validation loss being slightly higher than the training loss suggests only very slight overfitting.
- The absence of significant divergence between the two curves indicates good overall training stability and satisfactory generalization performance.

Table 1
Confusion matrix

	Actual Positive	Actual Negative
Predicted Positive	584 (TP)	7 (FP)
Predicted Negative	3 (FN)	641 (TN)

Table 2
Performance of the different models used

Model	Acc.	Recall	Prec.	F1
VGG16	0.967	0.967	0.969	0.968
ResNet50	0.827	0.852	0.822	0.837
Xception	0.985	0.988	0.985	0.986
MobileNetV2	**0.992**	**0.995**	**0.989**	**0.992**

Precision

The precision metric reaches very high values throughout the training process. The final training precision is 0.995, while the final validation precision reaches 0.991.

- The model effectively reduces the number of false positives.
- The fluctuations observed during validation remain low and within normal limits.
- The small gap between the training and validation curves indicates excellent generalization capability.
- The high precision values confirm the reliability of the model's positive predictions.

Recall

The recall metric demonstrates near-perfect performance. The final training recall reaches 0.998, while the final validation recall is 0.991.

- The model detects almost all positive cases, resulting in a very low false negative rate.
- The rapid improvement from the earliest epochs indicates strong learning capability.
- The stability of the curves after epoch 6 confirms the robustness of the trained model.
- The overall performance reflects an excellent balance between sensitivity and precision.

Next, Table 1 presents the confusion matrix results obtained from the classification of coccidiosis feces using the MobileNetV2 model.

The evaluation of the MobileNetV2 model is based on the following metrics, calculated from the values in the confusion matrix:

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{584}{584+7} = \frac{584}{591} = 0.98 \tag{1}$$

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{584}{584+3} = \frac{584}{587} = 0.99 \tag{2}$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = 2 \times \frac{0.98 \times 0.99}{0.98 + 0.99} = 0.99 \tag{3}$$

7. Discussion and Comparison with Existing Work

The results indicate that MobileNetV2 is the best-performing architecture among the evaluated models, achieving an accuracy of 99.2%, a precision of 98.9%, a recall of 99.5%, and an F1 score of 99.2%. A comparison with existing work highlights the competitiveness of the proposed approach. Indeed, [5] achieved accuracies of 95.01% with VGG16, 95.45 % with InceptionV3, 98.02% with MobileNetV2, and 98.24 % with Xception for classifying avian diseases based on droppings images, with F1 scores exceeding 75% for all models. Meanwhile, [6] reported an overall accuracy of 98.7% using a YOLOv3-based system dedicated to the detection of multiple avian diseases. The performance achieved in our study is therefore slightly higher than that reported in these studies.

These results can be explained by the use of a dataset specifically dedicated to coccidiosis detection, as well as by the various preprocessing steps applied to improve image quality and reduce class imbalances. Furthermore, unlike certain approaches relying on laboratory-based microscopic analyses [7], the proposed solution directly utilizes images acquired in the field using a smartphone. Consequently, the main contribution of this work lies not only in its high classification performance, but also in the practical deployment of the model in a mobile application, enabling early, rapid, and accessible detection of coccidiosis for poultry farmers under real-world conditions.

8. Conclusion and Future Work

This study presents a smart mobile app that enables the automatic detection of avian coccidiosis using images of droppings. The results demonstrate the potential of deep learning in the field of poultry farming. Looking ahead, we plan to improve and expand the dataset, incorporate other avian diseases, and deploy the solution in large-scale poultry farms. We also aim to enable poultry farmers to access our solution without an internet connection and to collaborate with national organizations such as Healthy and Sustainable Production of Eggs and Chicken in Modern Poultry Farming in Benin, as well as with international organizations such as the Food and Agriculture Organization of the United Nations (FAO).

Declaration on Generative AI

During the preparation of this work, the author(s) used ChatGPT in order to: translate part of the manuscript from French to English and perform grammar and spelling checks. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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