Hybrid Optimization of Coccidiosis Chicken Disease Prediction, Detection and Prevention Using Deep Learning Frameworks

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Abstract

Poultry farming is one of the thriving businesses in Kenya, therefore, playing a crucial role in the economy and the food value chain. Most of the farmers are small scale while a good number practice large-scale farming. Egg-laying birds are the most preferred as a result of the high profits gained from egg sales. However, various stresses including disease outbreaks have greatly caused loss due to late detection and lack of systems to predict the diseases before the infections. Coccidiosis has been one of the most prevalent and highly contagious poultry diseases. As such, there is a need to address the challenges, by employing emerging technologies in a built environment. In this study, deep learning models were deployed in the TensorFlow framework to detect the onset of the disease. Due to the fast spread of the disease, an automated vaccination system was used to protect healthy birds from attaining the disease, and to adopt a robust prevention system, a disease prediction framework was deployed to alert farmers to adapt to better mechanisms. Different deep learning models were deployed and tested and their accuracies were compared to get a fully efficient model. A Convolutional Neural Network (CNN) ResNet50 model showed the highest accuracy of 96% through the transfer learning technique. The deployed automatic vaccination system revealed high efficiency in releasing the right dose amounts after the disease is detected. Therefore, the Integration of engineering technologies to foster automated systems will not only ensure food security in poultry farming but also open up more industries to build these systems for the long-term benefit of farmers.

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1 Introduction

Coccidiosis poultry disease is one of the most important diseases caused by protozoans of the genus Eimeria which is mainly transmitted via the fecal-oral route. Due to its fast spread, poultry production is affected in a great way leading to losses and a threat to food security. In the event of an outbreak, severe losses are incurred attributed to the high cost of treatment, isolation of affected birds, and low-quality produce from the birds(1). This, overall, negatively affects the economy, export markets, loss of labor when the birds die massively, and spiking in eggs and chicken meat prices resulting from reduced production. As is the case with all other diseases, early diagnosis of coccidiosis disease would greatly help to offset the cost burden to farmers and also minimize the occurrence of zoonotic diseases to the consumers. However, the available conventional techniques of diagnosis which are mainly sound distinctions and visual observations, are time-consuming, labor-intensive, and inaccurate diagnosis by the farmers(2). Additionally, veterinarians may not be flexible enough to cater to the increasing poultry farming activities. Therefore, these conventional methods would be ineffective and unreliable for early detection of coccidiosis.

This study presents a deep learning machine vision-based early detection, prediction and auto vaccination technique to aid poultry farmers tackle the disease. Deep learning is a subset of machine learning inspired by the anatomy of the human brain and has recently gained application in agriculture. Its algorithms use multi-layered neural networks which are complex and whose abstraction levels improve step by step through non-linear transforms of the data inputted(3). The detection was aided by Convolutional Neural Networks (CNNs) which are the most effective and versatile deep learning architectures. They work by the principle of mimicking the human brain thus being able to interpret things the same as humans would, and even better. They have gained much attention and popularity because of their multi-later processing ability, less computation power is needed, and permit extracted features to be optimized. Therefore, they allow the computer system to capture only the required data, classify and recognize automatically, and hence trigger an action to be done as per the data captured.

Training of a deep learning model required a large amount of data and this may increase the cost of the system. A transfer learning approach was adopted which refers to the application of a known CNN model used in another classification task and applying it to be used in the new task(4). Some of the pre-trained models include ResNet50, XceptionNet, VGG19, and InceptionNet. This allows training of the model with little data and thus reduces computation power and development time. Transfer learning in a great way, helps to reduce overfitting or underfitting of the model.

Embedded systems are computer hardware systems embedded with software to perform specific tasks with the aid of a microcontroller(5). They help to integrate and deploy the trained Deep Learning model to be used for detection and auto-vaccination. These systems are mainly managed by digital signal processors (DSP), microcontrollers, Field programmable gate arrays, and gate arrays. These systems are incorporated together with components dedicated to handling mechanical and electrical interphase.

Several studies have been carried out to explore the use of image datasets for either recognition, classification, or segmentation.(3) Demonstrated a poultry disease detection model using Transfer Learning. The model gained an accuracy of 94%, outperforming Resnet, VGG, and MobileNet CNN architectures. However, this research did not show ways to tackle the disease after detection unless under human intervention. In another study, Support Vector Machine was used to demonstrate an early diagnosis and warning algorithm for broilers who were sick(6). The technique employed was to extract the posture of healthy and sick birds following the establishment of eigenvectors. Predictions were done after analysis of the bird's posture. The average accuracy obtained from this study was 91.5% but on the incorporation of all features, an accuracy of 99.5% could be achieved. However, the study focused primarily on poster-based techniques which may give false positive error for instance when the birds are just resting. In a similar study, carried out research to demonstrate chicken disease detection using a CNN model developed to detect and diagnose three types of chicken diseases using fecal images(4). Different models were trained which include VGG16, Xception, InceptionV3, and MobilenetV2. The model was deployed in smartphones as a diagnostic tool with MobilenetV2 attaining the highest accuracy. However, this research was only limited to classification alone.

The objective of this study, therefore, is to develop a novel system to predict, detect and automatically give vaccinations to the birds to protect them from contracting the disease with minimal or no human intervention. This will be enabled by fecal images of birds suffering from coccidiosis.

Figure 1: Sample images from dataset

2 Materials and Methods

2.1 Dataset

For purposes of this study, fecal images of coccidiosis were obtained from Kaggle Datasets and processed for purposes of training the model. Kaggle is a public online community that offers open-source datasets for deep learning. The dataset contained 2476 colored images of coccidiosis each of size 224 by 224 pixels and 2404 images of healthy fecal matter with similar properties as those of coccidiosis, which were all labeled and annotated for training. This dataset from Kaggle was obtained from farmers of poultry from both indigenous and cross-breeds of chicken. In its establishment, fecal samples were collected and analyzed in the laboratory to ascertain the accuracy of the data. Animal health professionals were also involved to verify the dataset before it was released for use to the public.

To develop a fully versatile and accurate model, different architectures designed for image classification were used, both in training and testing. These were Resnet50(7), VGG19(8), Xception(9), and MobilenetV2(10). VGG19 is an image classification model which is an improvement of its predecessor VGG16. This convolutional Neural Network (CNN) contains up to 19 layers and it is trained on the ImageNet which contains 1000 classes. Due to diminishing gradient which results in the decrease of the model's depth, VGG19 is difficult to train. However, it has the best feature extraction characteristics. To address the issue of diminishing gradient, Resnet 50 model was proposed. This allows CNN to go much deeper. It also consumes less training memory although it has many layers compared to VGG19. MobilenetV2 is also trained on ImageNet which is considered a lightweight model due to its high performance and efficiency in deployment on mobile devices. It is mainly made up of superficially separable neural network layers which are made from depth-wise differentiable convolution filters. One convolution filter with one-to-one convolutions serves as the mechanism for each input network. In a study conducted, Resnet 50, MobileNet, and VGG 19 pre-trained models were compared for the identification of pneumonia disease(11). The accuracy of the architectures was 87%, 92%, and 90%, respectively. This explains that not each architecture performs well in every problem. (3) proposed the leverage on the use of the transfer learning approach and finetuning the model weights instead of training the model from scratch since this not only improves the accuracy of the model but also reduces the amount of time used for training the model.

2.1.1 Model's Architecture

The transfer learning approach was used in the training of the models. Images of size 224 by 224 pixels were fed into the convolution layers as inputs for ResNet50, MobilenetV2, and VGG19. An image size of 299 by 299 pixels was used for the Xception model architecture. The batch size of the input images was set to 32. After the convolutional layer, which operates over a 2 by 2-pixel window, is the max-pooling layer, which has filters with narrow receptive fields of 3 by 3. A combination of these layers takes place leading to the formation of a single block which is applied iteratively while raising the network's filler depth to integer values such as 32, 64, 64, 128, 128, 256, 256, and 512 which makes it a full block convolution. Similar padding is applied throughout the different model training to maintain the width and height shape of the output. Adam optimizer was used for VGG19, MobilenetV2, and Resnet50 with a learning rate of 0.001 to minimize the error. The Sparse

Table 1: Model's Performance

Model	Test Accuracy (%)	Validation Accuracy (%)
VGG19	89.15	90.63
Resnet50	96.32	95.96
MobileNetV2	93.95	93.75
Xception	96.14	96.75

Table 2: ResNet50 Parameters

Parameter	Value
Learning Rate	0.0001
Number of Epochs	10
Hidden Layers	256
Drop-out	0.2

Categorical Crossentropy probabilistic class was used to compute the loss between the predictions and the labels and SoftMax activation function in the output layer.

2.2 Autovaccination

Embedded systems offer a novel way of deploying deep learning models in real life and using them to make inferences. In this setup, Raspberry Pi 4 model B, 4Gb RAM was used to deploy the TensorFlow Lite quantized model. The micro-submersible pump was connected to a 5V relay module to offer protection to the Raspberry Pi board. The VCC port for the relay module was connected to General Input and Output (GPIO) pin 17 which was configured to give a signal whenever coccidiosis was detected. To get the image data, a USB webcam was connected to the Pi USB 3.0 port.

3 Results and Discussion

3.1 CNN Model

The dataset obtained from Kaggle with four classes was used to develop the Convolutional Neural Network to detect and classify coccidiosis disease from infected fecal images. From the different architectures that were used, ResNet50 produced the top performance of 96.32% after finetuning the model. Before finetuning was done, the model produced an overall test accuracy of 94% using the transfer learning approach. To increase this accuracy, finetuning was done for additional 10 epochs and a learning rate of 0.0001 to minimize the overfitting of the model. The layers of the base model were also unfrozen by enabling `base_model.trainable= true.` Accuracy scores for the other models were MobilenetV2 model 93.95%, VGG19 model 89.15%, and Xception model 96.14%. However, it is worth noting that the Xception model performed closely to ResNet50. Table 1 shows the performance of the models after finetuning. The parameters for the best-performing model were as shown in table 2. The training and loss curves on Resnet50 model are shown in figure 2 and 3 respectively

3.2 Autovaccination

The main goal of this research seeks to develop an autovaccination dispensation system, the best-performing model was saved and converted to a TensorFlow lite (tf lite) version which was deployed on a raspberry pi. Tf lite is a lighter version of the TensorFlow model that is ideal for resource-constrained devices such as raspberry pi. To obtain the tf lite file, `tensorflow.lite.TFLiteConverter` instance was used to convert the saved model. The resulting tf lite file was optimized for size and yielded 21 MB of data. The file was also normalized and the class labels were added to the metadata. Deployment done and tested on the Python OpenCV library showed greater performance in the detection of coccidiosis in real-time. Confidence scores obtained were 97% in a bright-lit environment and 67% in a partially dark room. The embedded system was also able to identify multiple instances of the disease from the same image input. With the

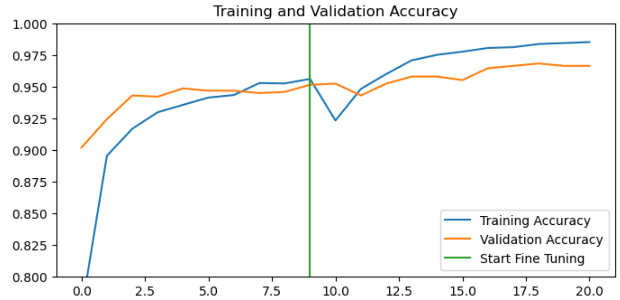

Figure 2: Training curve

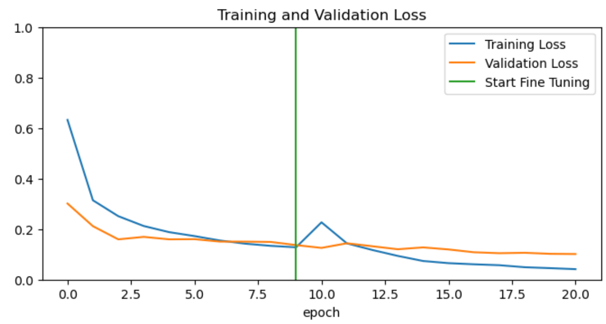

Figure 3: Loss curve

instances of the disease detected, the micro-submersible pump through the relay module dispensed the vaccine portions which were calibrated. Calibration was done to match the time taken for the pump to operate once the disease instance is detected. This approach was best in that the flow rate is known per unit time and the speed of the pump motor was constant. This alludes that the required dosage of the vaccine is equivalent to the dispensing time. Farmers, however, have to prepare the vaccine and store it carefully in a tank where the pump can be installed. Reapplication time of the vaccine was set to one week after which any recorded instance of the disease would trigger another application of the disease.

4 Conclusion and Future Scope

As a result of using deep learning technology to identify coccidiosis disease in chicken houses, vaccination systems can be used to counter the onset of the disease and hence minimizing on losses incurred by the mass death of chickens. Instances of the disease occurrence can also be recorded and reported to the farmer to enable them to make informed measures and decisions on their rearing practice. Leveraging artificial intelligence comes in handy in that farmers can boost and expand their production with minimal reduction in losses anticipated as a result of a disease outbreak. In combination with other systems, this paper proposes a framework where the integration of other systems can be combined to build intelligent chicken farming systems while leveraging deep learning and computer vision. These include; live streaming of the detections made, integration with feeding systems, and recommendations to farmers based on data collected.

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