MOBILE-BASED MACHINE LEARNING SYSTEM TO RECOGNIZE POULTRY DISEASES.

CASE STUDY: NEW CASTLE DISEASE, SALMONELLA, AND COCCIDIOSIS

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ABSTRACT

This project focuses on the design of a mobile-based machine learning system for the recognition of poultry diseases in Uganda. The livestock sector in Uganda is on the rise and the fast-growing population requires improved poultry production. However, several constraints, including diseases, lack of drugs, improper farm management, and wrong motives, affect increased production. The use of artificial intelligence for real-time disease recognition in poultry is promising due to its non-intrusive properties and ability to provide a wide range of information. The system uses TensorFlow to analyze and train the model which is later deployed into a mobile application with the help of Android Studio. The literature review highlights the main concepts of poultry diseases and the use of machine learning methods in poultry. The result is a system that will have reduced operating costs and improved disease detection for farmers.

Key terms: Mobile-based machine learning system, recognition, analyze, train and Deployment.

I. INTRODUCTION

The livestock sector in Uganda contributes 3.2% to the national gross domestic product (GDP) and is projected to be rising.[1] A report in 2009 showed that 4.5 million households (70.8%) owned livestock or poultry

In the recent past, a large number of people in and around Kampala and other major towns have taken up poultry farming. To meet the requirements of the country's fast-growing population, there is a need for improved and increased poultry production. However, several factors put a great constraint on increased production in the country. These factors are mainly disease, lack of appropriate drugs and vaccines, improper management of farms, and wrong motives for poultry farming. Diseases and pathological conditions affecting poultry are many and varied.[2]

Some of the common diseases that bring a setback in poultry farming include;

Newcastle, Coccidiosis, Salmonella, Aspergillosis, Gumboro disease, and so on.[3], [4]

Respiratory diseases such as Newcastle require early detection so the whole poultry farm is not lost in a short time. Having a system that would detect the disease increases production.[5]

With the current development in information technologies, Artificial intelligence has become a promising tool in the real-time recognition of poultry disease monitoring systems due to its non-intrusive and non-invasive properties and ability to present a wide range of information. Hence, we will use the Tensor flow to deploy the d into the mobile application, we will be able to identify some of the most common poultry diseases.

II. LITERATURE REVIEW

2.1 MAIN CONCEPTS OF THE PROJECT

2.1.1 Poultry Diseases overview

Coccidiosis

Chickens' intestinal systems are infected with parasites of the genus Eimeria, which cause coccidiosis. The conventional diagnostic approach includes examining the digestive tract and/or counting the number of occysts (expressed as occysts per gram opg) in the stool to calculate the lesion scores.[6]

Salmonella

Salmonella spp are bacterial pathogens of the genus Salmonella that cause diseases in chickens, other domestic animals, and humans. The polymerase Chain Reaction (PCR) procedure is used for the detection and identification of various Salmonella strains.[7]

Newcastle Disease

Newcastle disease is an acute viral infection in poultry and other bird species caused by avian paramyxovirus serotype 1 (APMV-1) viruses. Newcastle disease virus (NDV), APMV-1 is dragonized by serology or virus isolation tests or real-time reverse-transcription PCR procedure.[8]

These diseases can be diagnosed early using machine learning and deep learning methods.

2.1.2 Machine learning methods in poultry

(a)Recently, various research has suggested using machine learning to identify diseases in chickens.[8] To categorize fine-grained abnormal broiler droppings photos as normal and abnormal, Wang et al. (2019) suggested disease an automated broiler digestive detector based on deep Convolutional Neural Network models, Faster R-CNN, and YOLO-V3. On the testing data set, faster R-CNN scored 99.1% recall and 93.33% mean average precision, whereas YOLO-V3 attained 88.7% recall and 84.33% mean average precision.

Weakness

The study by Wang et al. (2019) advances the creation of an automatic, non-contact model for recognizing and categorizing irregular droppings in broilers with digestive disorders, but a practical solution is still needed for the early diagnosis of poultry diseases.

(b)In another study, Okinda et al. (2019) proposed a machine vision-based broiler chicken monitoring system in a different study. Based on mobility features and 2D posture shape descriptors, feature variables were derived. Then, two sets of classifiers were created, one using all the feature variables and the other just using the posture shape descriptors. With an accuracy of 0.975, the Support Vector Machine (SVM) with a radial basis kernel function surpassed all other models.

Weakness

Even though the suggested method continually and non-intrusively predicts the occurrence of sickness, it still has to be validated with various chicken breeds and infection types.

(c)Support Vector Machine (SVM) was also used in another study that proposed an early warning algorithm for detecting sick broilers. The posture features of healthy and sick chickens were extracted, the eigenvectors were established, the postures of the broilers were analyzed by machine learning algorithms, and the diseased broilers were predicted.

Weakness

Accuracy rates of 84.2, 60.5, and 91.5% were obtained, but using all the features can yield an accuracy rate of 99.5%. Even though the study proposed a suitable method for small-sample learning and disease diagnosis, the focus was only based on a posture-based algorithm.

III. SYSTEM DESIGN

The proposed system utilized a machine learning model that was built and updated using python programming. Once the model was trained, it was converted to TFLite format, which is a lightweight format that allows the model to be run on mobile devices. This TFLite model was then integrated into an android app using ML kit and Android Studio.

Block diagram for the System.

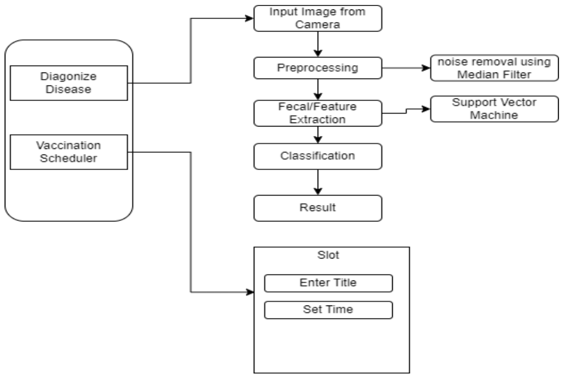


Figure 1. Block Diagram

System Flow Chat

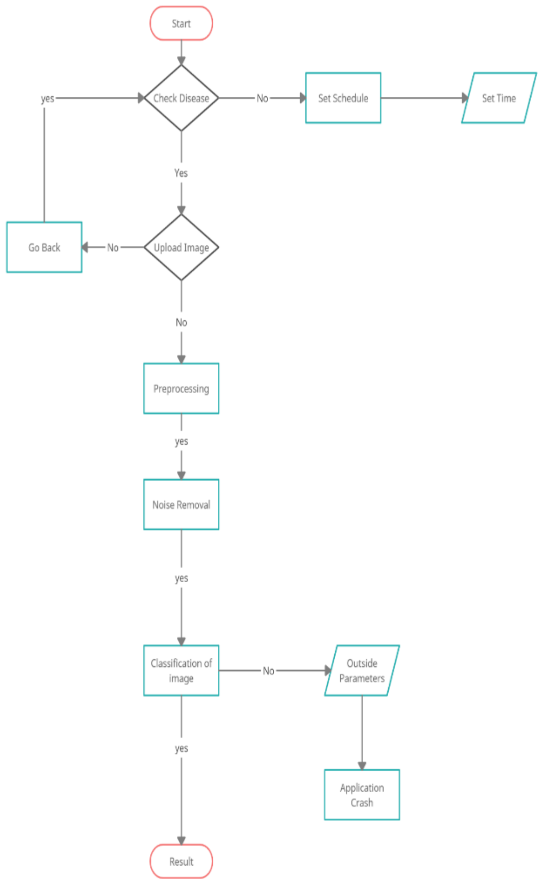


Figure 2. Flow Chart

Sample of test images displayed using python in Google Colab

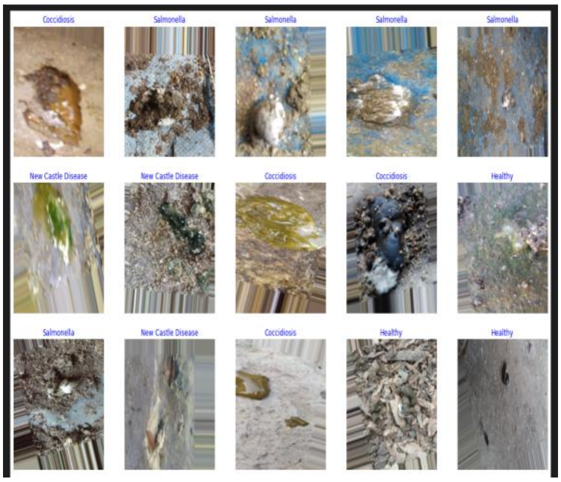
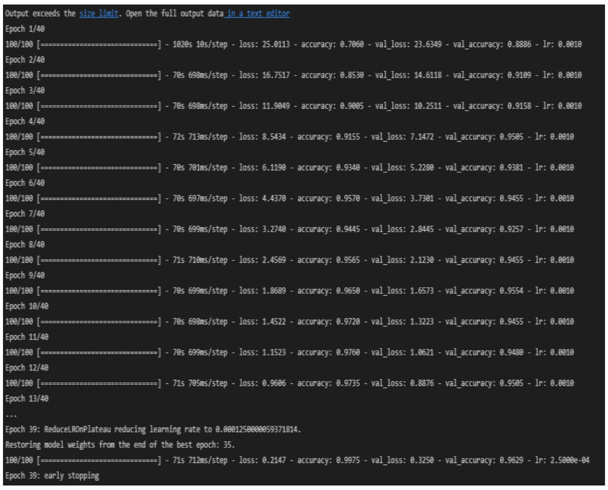


Figure 3. Sample images generate for output from the dataset

The model was trained to be able to distinguish the fecal features.Below is a figure showing how it was done.



```
Output exceeds the size limit. Open the full output data in a text editor
Epoch 1/40
100/100 [==============================] - 1020s 10s/step - loss: 25.0113 - accuracy: 0.7060 - val_loss: 23.6349 - val_accuracy: 0.8886 - lr: 0.0010
Epoch 2/40
100/100 [==============================] - 70s 698ms/step - loss: 16.7517 - accuracy: 0.8530 - val_loss: 14.6118 - val_accuracy: 0.9109 - lr: 0.0010
Epoch 3/40
100/100 [==============================] - 70s 698ms/step - loss: 11.9049 - accuracy: 0.9005 - val_loss: 10.2511 - val_accuracy: 0.9158 - lr: 0.0010
Epoch 4/40
100/100 [==============================] - 72s 713ms/step - loss: 8.5434 - accuracy: 0.9155 - val_loss: 7.1472 - val_accuracy: 0.9505 - lr: 0.0010
Epoch 5/40
100/100 [==============================] - 70s 701ms/step - loss: 6.1190 - accuracy: 0.9340 - val_loss: 5.2280 - val_accuracy: 0.9381 - lr: 0.0010
Epoch 6/40
100/100 [==============================] - 70s 697ms/step - loss: 4.4370 - accuracy: 0.9570 - val_loss: 3.7301 - val_accuracy: 0.9455 - lr: 0.0010
Epoch 7/40
100/100 [==============================] - 70s 699ms/step - loss: 3.2740 - accuracy: 0.9445 - val_loss: 2.8445 - val_accuracy: 0.9257 - lr: 0.0010
Epoch 8/40
100/100 [==============================] - 71s 710ms/step - loss: 2.4569 - accuracy: 0.9565 - val_loss: 2.1230 - val_accuracy: 0.9455 - lr: 0.0010
Epoch 9/40
100/100 [==============================] - 70s 699ms/step - loss: 1.8689 - accuracy: 0.9650 - val_loss: 1.6573 - val_accuracy: 0.9554 - lr: 0.0010
Epoch 10/40
100/100 [==============================] - 70s 698ms/step - loss: 1.4522 - accuracy: 0.9720 - val_loss: 1.3223 - val_accuracy: 0.9455 - lr: 0.0010
Epoch 11/40
100/100 [==============================] - 70s 699ms/step - loss: 1.1523 - accuracy: 0.9760 - val_loss: 1.0621 - val_accuracy: 0.9480 - lr: 0.0010
Epoch 12/40
100/100 [==============================] - 71s 705ms/step - loss: 0.9606 - accuracy: 0.9735 - val_loss: 0.8876 - val_accuracy: 0.9505 - lr: 0.0010
Epoch 13/40
...
Epoch 39: ReduceLROnPlateau reducing learning rate to 0.0001250000059371814.
Restoring model weights from the end of the best epoch: 35.
100/100 [==============================] - 71s 712ms/step - loss: 0.2147 - accuracy: 0.9975 - val_loss: 0.3250 - val_accuracy: 0.9629 - lr: 2.5000e-04
Epoch 39: early stopping
```

Figure 4. Training process

Below is a classification report generated in google colab to provide details of the data set.

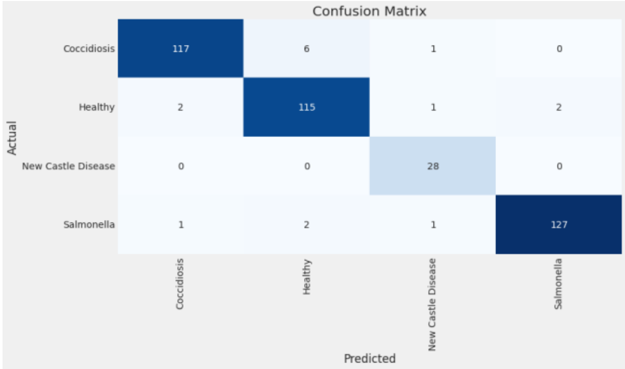


Figure 5. Confusion Matrix

Application View from the phone interface

a) First Interface

Figure 6 First interface on loading the application

b) Check for Chicken Disease

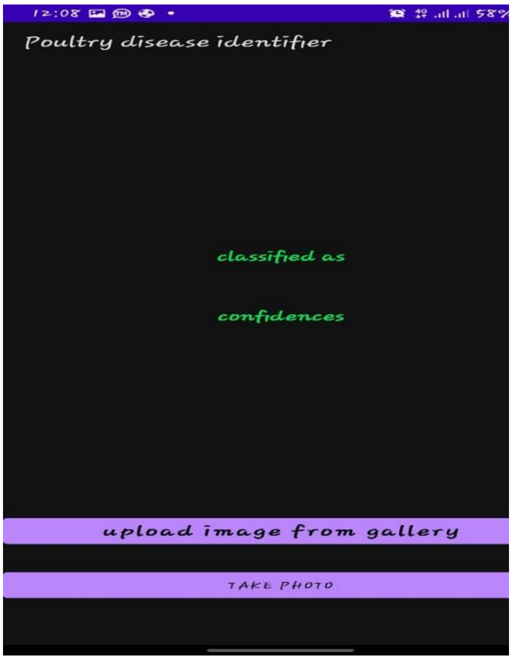


Figure 7 . Before Loading image

c)After loading image

Figure 8 Salmonera detected

IV. RESULTS

The image was uploaded to the mobile app for disease recognition among the three diseases under study. Results are shown below;

Figure 9 Salmonera detected

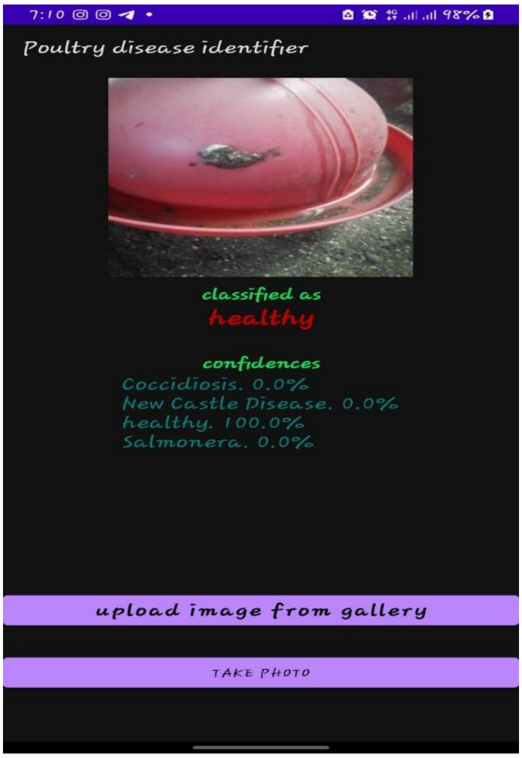


Figure 10 Healthy

IV. CONCLUSION

The developed system ensures that there is minimal wastage of time like agricultural officers coming and first collecting a number of farmers to be talked too hence costs attached. The developed system is easy to access information by the farmers and it is a cheaper method compared to other existing systems. Despite the challenges faced during the development of this project prototype, at least most of the stated specific objectives were achieved.

V.REFERENCES

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