Image-Based Poultry Disease Detection Using Deep Convolutional Neural Network

Hope E. Mbelwa & Dina Z. Machuve

School of Computational and Communication Sciences,
The Nelson Mandela African Institution of Science and Technology,
P.O.BOX 447, Arusha, Tanzania.

Introduction

Global poultry production is forecast to rise by 2.6% to 137 million tonnes, due to the high demand from consumers and food safety [2]. In Tanzania, poultry farming is economically significant supporting up to 37 million households. It is mostly practiced traditionally and is a source of food and income at family level [4]. However, farmers face many challenges including diseases. Late diagnosis of the diseases highly affects production. The recent use of deep learning in disease detection motivates the need to contribute to robust diagnostics in chicken diseases [5].

Problem Statement

- Poultry productivity gradually decreases by 2.6% annually in Tanzania mainland due to diseases affecting the chicken [4].
- Coccidiosis, Salmonella and Newcastle are devastating diseases [1].
- Existing methods of poultry diseases diagnostics are based on laboratory procedures that are time consuming (3 - 7 days) and expensive.
- Lack of access to reliable sources of information.

Objectives

1. To develop a model for early detection of poultry diseases using deep convolutional neural network for poultry farmers in Tanzania.
2. To review existing approaches for poultry diseases diagnostics and identify the requirements for the proposed model.
3. To evaluate the performance of the developed model for poultry diseases diagnostics.

Materials and Methods

Data for the study (fecal images) were collected from poultry farms in Arusha, Kilimanjaro and Manyara regions. It was labelled, processed and split into training and test sets which were then used to train Convolutional Neural network models (CNN's). An optimized model for prediction of the diseases was developed.

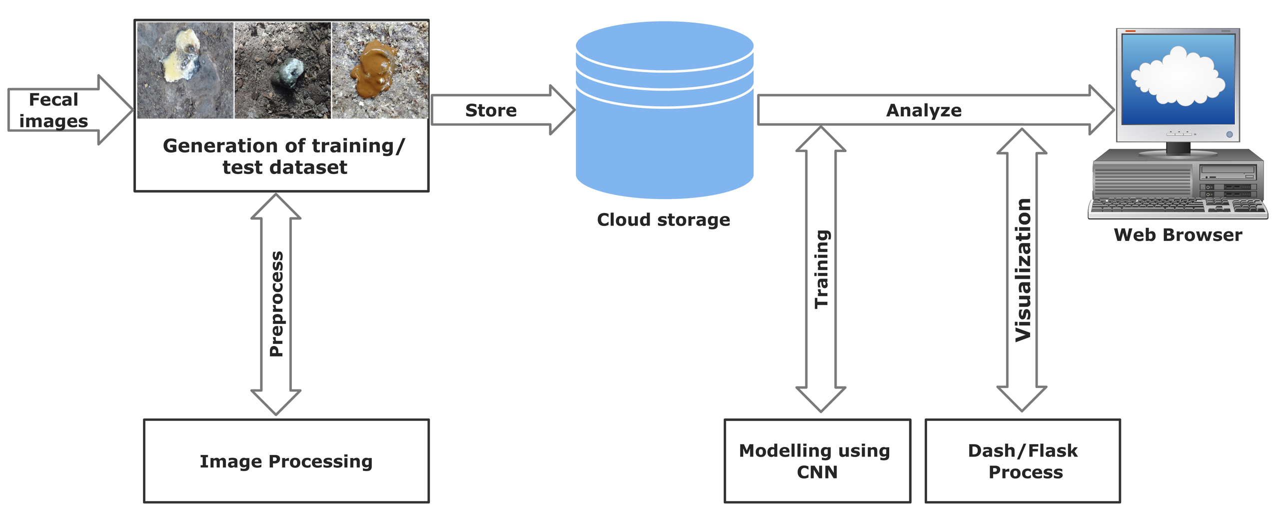

Figure 1: Conceptional framework

Class	Image in each class	Training	Validation	Test
Health	508	305	102	102
Coccidiosis	516	310	103	103
Salmonella	566	340	112	113
Total Images	1590	955	317	318

Table 1: Dataset splitting Training, Validation and Testing sets

Results

We evaluated the models using the Accuracy and Log loss metrics. The XceptionNet model outperformed the other models with an accuracy of 94% and a log loss of 0.15. The table below indicates performance comparison for different models trained on the dataset. The graphs show training and validation accuracy and loss plots of the XceptionNet model.

Model	Log Loss	Validation Accuracy	Validation Loss
VGG 16	0.35	0.8933	0.3522
Resnet 50	4.80	0.3133	1.1131
MobileNet	0.89	0.6833	0.9005
XceptionNet	**0.15**	**0.9400**	**0.1610**
CNN	0.20	0.9267	0.2282

Table 2: Performance comparison for different algorithms

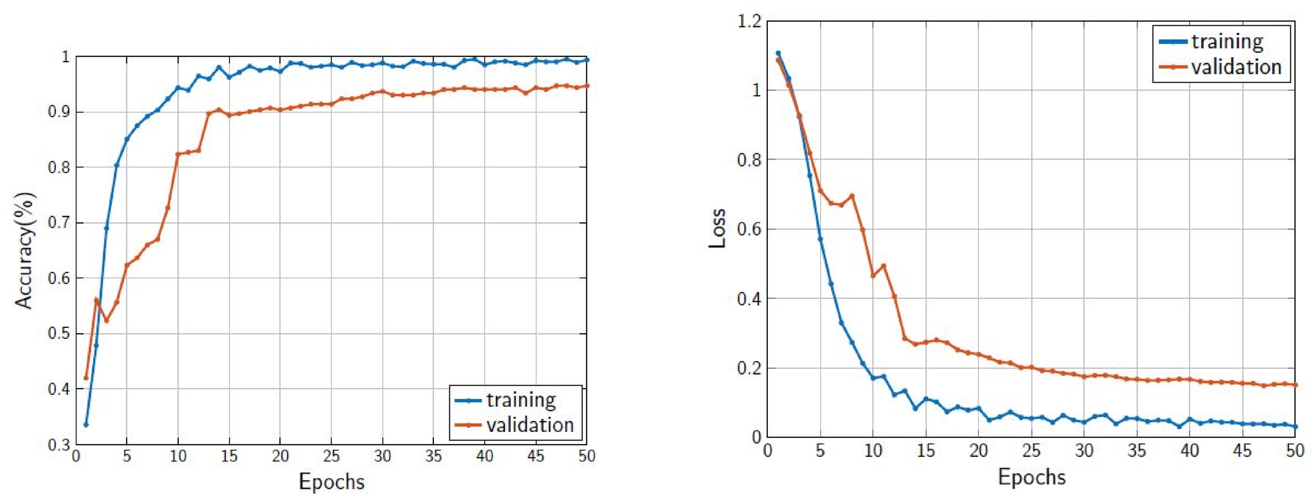

Figure 2: The training and validation set accuracy and loss of the XceptionNet evaluated on the dataset

Conclusions

- We observe that key elements that can improve performance of early detection of chicken diseases are the use of computer aided instruments and accurate data.
- We generate a supervised learning model that predicts three categories Healthy, Coccidiosis and Salmonella.
- Experimental findings indicate that our developed model works well on disease detection in chicken and can be used for robust diagnostics.

Recommendations and Future work

- We recommend stakeholders inclusion to engage in collection of more data in order to expand the data set repository.
- Deploying the model in the mobile application with additional features like recommendation systems to allow easy interaction of the stakeholders.
- Future research can be conducted using the dataset.

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