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Image Detection and Classification of Newcastle and Avian Flu Diseases Infected Poultry Using Machine Learning Techniques

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Abstract

The frequency at which diseases occur in poultry nowadays is staggering. Poultry diseases, such as Newcastle disease, Avian Influenza etc. usually brings about serious economic losses to poultry business owners and also to farm produce consumers. Prompt warning and identification of emerging poultry disease outbreaks is of utmost importance in the poultry business. Digital imaging technology and machine learning algorithms have made room for the effective observation / monitoring of poultry health status via surveillance cameras online and in real time has proven to be an effective way to prevent large-scale outbreaks of diseases. To analyze the images of healthy and diseased birds, images of healthy birds were taken directly from poultry farms using different camera devices such as Digital cameras, Mobile Phones etc. The first step we took was to transform the images into a fixed sized length of dimension (64, 64, 3). The images were then augmented. Firstly, to help increase the size of the dataset, Secondly, to create variations that will better capture reality, so as to increase the ability of the model to generalize better and predict out of sample data more accurately. Other augmentation carried out on the training set include Scaling, Rotation, Shifting, Zooming and Flipping (horizontally). Using the Models implemented in this research, accuracy rates of 95% and 98% are obtained. The results show that digital image processing and the machine learning algorithm implemented in this research can effectively detect and classify sick/diseased birds from healthy Birds whilst giving high accuracy and good performance which will aid in giving early warning signals. This research can serve as a reference for the intelligent detection and classification / identification of sick birds from healthy birds.

Keywords*: Image detection and classification, Newcastle disease, Avian flu disease, Machine learning*

1. INTRODUCTION

Livestock production accounts for close to Fifty percent 50% of the world's agricultural gross domestic product. It is also the source of livelihood for more than 1.3 million people in developing countries [1]. Because of these reasons, adequate care has to be taken whilst breeding livestock. Poultry Birds usually comes across two major Diseases that are visible to the eyes which include Newcastle Diseases and Avian flu Diseases.

1.1 Newcastle Disease

Newcastle disease is a Global problem and has been a devastating disease of poultry, and in many countries the disease remains one of the major problems affecting existing or developing poultry industries [2]. Exotic Newcastle Disease virus which is the most devastating form of the virus, has been eradicated within the United State and Canada. The milder variants of Newcastle are kept under control using vaccines.

1.2 Avian Influenza

Avian influenza (AI) is an extremely contagious infection which may go viral thereby causing up to 100 percent mortality in domestic chickens or turkeys. This infection/disease is caused by a virus belonging to the family Orthomyxoviridae. When this virus infects domestic poultry (chickens or turkeys) they often transform into different strains and virulent disease arises in these birds that are severely pathogenic [3].

In recent years, a lot of researchers have tried reducing mortality rate of the birds due to the

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Avian flu diseases and Newcastle diseases. Various methods have been employed with little or no improvement. Due to this problem, Big and small poultry farmers have suffered staggering financial losses to the outbreak of these diseases.

This research will prove to be useful to the world of agriculture by increasing accuracy in disease detection in the poultry and also making up for efficiency that humans may lack. Various Intelligent methods have been used to tackle detection of diseases in poultry birds like using the poultry sound to detect change in body system.

In detecting content in images, Convolution Neural Network is the most popularly used model. This research has developed a model using CNN that can detect Newcastle and Avian flu abnormalities in the images and therefore detect sick birds and classify them from non-sick ones.

The aim of this research is to develop a model that can detect sick poultry birds using image recognition and classify the sick from non-sick poultry bird using convolution neural network
The objectives include:

- Development of a model that can detect and classify sick birds from non-sick birds using CNN.
- Implementation of the model.
- Testing and evaluation of the model.

2. RELATED WORKS

Sadeghi, *et al*. [4] used chicken vocalization which was recorded every morning using a microphone and a data collection card under equal and controlled conditions. Sound signals were investigated in time domains, and 23 features were selected. Using Fisher Discriminate Analysis (FDA), five of the most important and effective features were chosen. Neural Network Pattern Recognition (NNPR) structure with one hidden layer was applied to detect signals and classifying healthy and unhealthy chickens. Firstly, this neural network was trained with 34 samples, after which eight samples were tested for accuracy. Classification accuracy was 66.6 and 100% for days 16 and 22 respectively.

Xiaolin Zhuang *et al*. [5] analyzed the postures of healthy and sick broilers, by inoculating bird flu virus intranasally into healthy broilers manually. The recognition effects of several commonly used machine learning algorithms are compared with the Support Vector Machine (SVM) model obtaining an accuracy rate of 99.469% on the test samples, which is superior to those of the other machine learning algorithms.

Jintao Wang *et al*. [6] proposed an automated broiler digestive disease detector based on a deep Convolutional Neural Network model to classify fine-grained abnormal broiler droppings images as normal and abnormal (shape, color, water content, and shape & water). Droppings images were collected from 10,000 25-35-day-old Ross broiler birds reared in multilayer cages with automatic droppings conveyor belts. For comparative purposes, Faster R-CNN and YOLO-V3 deep Convolutional Neural Networks were developed. The performance of YOLO-V3 was improved by optimizing the anchor box. Faster R-CNN achieved 99.1% recall and 93.3% mean average precision, while YOLO-V3 achieved 88.7% recall and 84.3% mean average precision on the testing data set.

3. METHODOLOGY

The design and development of the model was performed using the python programming language and the Jupyter notebook development environment. The Jupyter notebook comes with libraries used in our design process.

a. NumPy: It is Base n-dimensional array package. Pandas Library is built on this Library.
b. SciPy: It's a fundamental library for scientific computing.
c. Pandas: It allows for data structure and analysis.
d. Matplotlib: It allows for comprehensive 2D/3D plotting.
e. Seaborn Library: This Library is used for data visualization and result presentation. It provides a high-level interface for creating attractive and information filled statistical graphics /Images.
f. Keras is known to be a very useful and easy-to-use free open-source Python library which is majorly used for the development and evaluation of many deep learning models. It makes use of the efficient numerical computation libraries, namely TensorFlow and Theano and permits the user to define and train neural network models with as little lines of code as possible.

3.1 THE SYSTEM MODEL

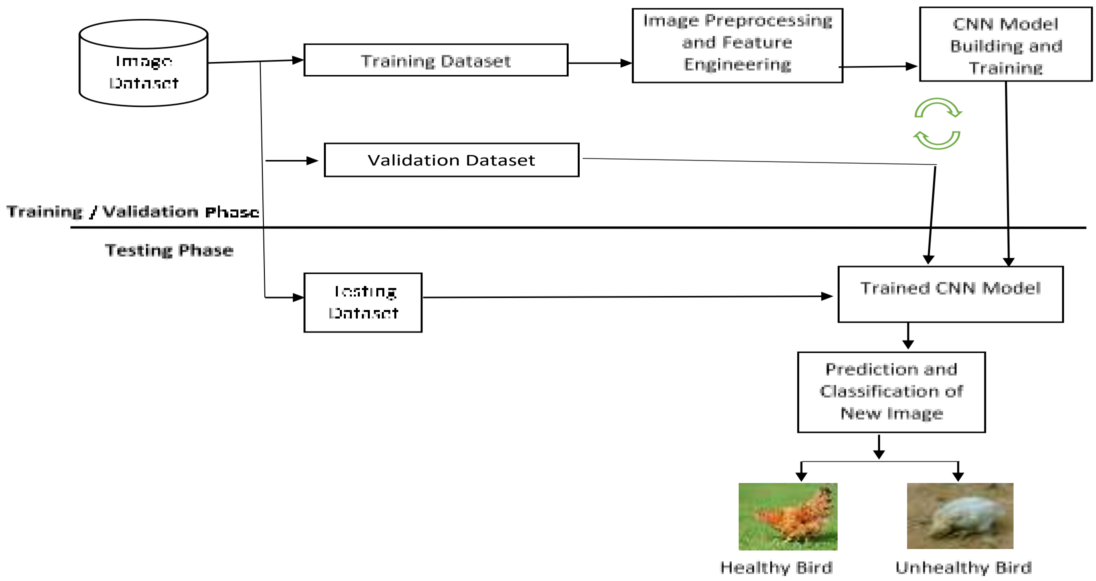

Figure 1. System Model

3.1.1 The System Model:

From Fig 1 above, the Image dataset depicts the total number of images to be used on the model and which was further broken down into three different sets namely Training, Validation and Testing datasets. The training dataset is then preprocessed whilst the feature engineering was also done at this stage after which the CNN model was then built and trained with the training dataset. The training and validation stages were repeated until a favorable result was achieved before finally using the Testing dataset on the trained CNN model which in turn predicts and classifies the image fed into it as either Healthy or Unhealthy.

3.2 Dataset Description

The dataset was gathered from various sources such as the internet, magazines, poultries etc. The bulk of the images of the healthy birds were gotten directly from the poultry farms where they were kept and pictures were taken using different camera devices such as Digital cameras, Mobile Phones etc. It was not possible to capture any images of sick/diseased birds at any of the farms as at the time of our visits. All the images of sick/unhealthy/diseased birds were downloaded over the internet. Downloading of images of more healthy birds was done directly over the internet while some were cropped out of other pictures that were also seen online. The total number of preprocessed images obtained was 733 belonging to both the sick and healthy birds. These datasets were divided into 70%, 20%, and 10% as training set, validation set and testing set respectively.

3.2.1 Input Dimension

The input images are of varying length because they were gathered from various sources and snapped using different camera devices. So, the first step taken was to transform the images into a fixed sized length of dimension (64, 64, 3).

3.2.2 Data Augmentation

The images were then augmented. Firstly, to help increase the size of the dataset, due to the limited available dataset for Avian-flu and Newcastle diseased birds. Secondly, to create variations that better captured reality, so as to increase the ability of the model to generalize better and predict out of sample data more accurately. Natural occurring scenarios involve objects in various lightening environment, background, occlusion, orientation, zoom, and so on. Other augmentation carried out on the training set include the following:

3.2.3 Scaling: scaling the input images' pixel value by 255 reducing it to values between 0 and 1. This was done to reduce computational complexity.

3.2.4 Rotation: Random rotation of the images by 10 degrees was done.

3.2.5 Shifting: The images were shifted horizontally and vertically by a factor of 0.1.

3.2.6 Zoom: Randomly zoomed some images by 0.1 and shear range by 0.2.

3.2.7 Flipping: Randomly flipped the images horizontally. No vertical flipping was performed since most sick birds can be identified using just that characteristic alone, augmentation was not done in a way that affected the performance of our model.

3.3 CNN Model Building and Training

Two CNN models with similar architecture but different optimizers was built and used in this research work. The preprocessed input Image was fed into Convolutional Neural Networks for training the CNN models to correctly classify a poultry bird as sick (Newcastle and Avian Flu infected) or healthy.

3.3.1 CNN Methodology (Model Configuration 1)

This is the first CNN model referred to as "model 1" and was built with "Adams" optimization algorithm and without a Dropout feature. The Dropout mechanism is a method of randomly turning off some nodes in CNN layers to prevent over-dependence of consequent layers on previous inputs.

a. Configuration 1

{ { (Conv2D(32, (60,60,1), (5,5)) + ReLU) + (Conv2D(32, (56,56,1), (5,5)) + ReLU) } + MaxPool2D((2,2), Stride(2,2)) } + { { (Conv2D(64, (26, 26, 1), (3,3)) + ReLU) +(Conv2D(64, (24, 24, 1), (3,3)) + ReLU)} + MaxPool2D(2, Stride(2,2)) } + FC(256) + Softmax(2)

3.3.2 CNN Methodology (Model Configuration 2)

While the second model referred to as "model2" was built with "RMSProp" optimization algorithm and Dropout layer added. This method increases variance and thereby prevents the model from over-fitting.

b. Configuration 2:

*{ { (Conv2D(32, (64,64,1), (5,5)) + ReLU) * 2 } + MaxPool2D(2, Stride(2,2)) + Dropout(0.25) } + { { (Conv2D(64, (32, 32, 1), (3,3)) + ReLU) * 2 } + MaxPool2D(2,Stride(2,2)) + Dropout(0.25) } + FC(256) + Dropout(0.5) + Softmax(2)*

Summary of the Implemented CNN Model Architectures.

To find the optimal parameters in our networks, two optimization algorithms were explored, namely, Adam and RMSprop optimizations. Using the same architecture above, two models were trained using each optimization algorithms for each model respectively. For the Adam optimizer, the default parameters as specified in keras framework were used. These default parameters had been confirmed to be the best by various researchers. The initial learning rate was set to 0.001, rho to 0.9, epsilon to 1e-8 and decay to 0.0 as parameters for RMSProp Optimizer

3.4 Training the Model

The preprocessed images obtained were 733 belonging to sick and healthy birds. These datasets were divided into 70%, 20%, and 10% as training set, validation set and testing set respectively.

The CNN models on the training set and the validation set were trained, based on the two (2) optimization algorithms. Training a CNN model involves two stages. The convolutions stage and the Fully-Connected Artificial Neural Network training stage.

The Convolutions stage involves extraction of distinguishing features (feature maps) of given image category through the repeated application of convolutions and Max Pooling. The fully-connected stage involves flattening all feature maps and then feeding it into a fully connected Neural Network.

Training a fully-connected ANN is the process of finding optimal weights that will produce the best prediction performance with minimal loss. This training involves two stages, namely Forward and Backward propagation.

In the forward propagation stage, weighs are uniformly initialized with some random weight values slightly greater than zero (0). Using these weights, the input values are subjected to a function (activation) which determines whether a node passes forward its value to the next layer of the network, until the output class is obtained.

The backward propagation stage involves adjusting the weights of a neural networks based on the loss obtained. Here, a loss is computed as the difference in the expected output and the actual output. The computed loss is the used to adjust the weights of the preceding layers on the basis of how much they affected the proceeding outcome. This process is repeated for a number of iterations (epochs) until optimal weights are obtained. In this work, the CNN models were trained using the architecture specified above for 30 epochs. To apply non-linearity, ReLU activation function was used to fully connected layer “FC” except the output layer where a “SoftMax” activation function was used for multiclass classification problem. “Categorical cross entropy” loss function was used to calculate the loss and “accuracy” as performance metric.

In the process of making the optimizer converge quicker / faster and nearest to the global minimum of the loss function, an annealing method of the learning Rate (LR) was used. The Learning Rates (LR) are the steps through which the optimizer walks through the 'loss landscape'. The higher the LR simply means that the bigger will be the steps and the quicker will be the convergence.

Unfortunately, the sampling was very poor with a high Learning Rate (LR) which could make the optimizer probably fall into a local minima. It is worthy of note that it is usually better to have a decreasing learning rate during the model training to reach efficiently the global minimum of the loss function. It is usually preferable for the learning rate to be decreasing during the training stage of the model in order for it to be able to reach the global minimum of the loss function efficiently. To keep the advantage of the fast computation time with a high LR, decreasing the LR dynamically was done Every X step (epochs) depending on its necessity (usually when there is no improvement on accuracy).

With the ReduceLROnPlateau function from Keras.callbacks, the LR was reduced by half when the accuracy did not improve after 3 epochs. More so, in order to reduce (optimize) computational resources, an early-stopping mechanism was used to stop the learning if the validation-loss is not reduced after 5 rounds, at which point it can be assumed the model is no more learning. This can also help prevent over-fitting.

3.5 Evaluation Metrics

a. Accuracy

This may be outlined as the total numbers of true negatives and true positives which is then divided by the total number of true negatives, true positives, false negatives and false positives. The true negative or true positives are points of data that our algorithm have correctly identified and classifies as false or true, respectively. While false positives or false negatives, are data points that the algorithm classified incorrectly.

b. Confusion Matrix

The Confusion Matrix is one which gives a matrix as output and describes the overall performance of the model. There are 4 important terms:

(i) TRUE POSITIVES: These are the cases where our prediction was a "YES" and the eventual output was also "YES".
(ii) TRUE NEGATIVES: These are the cases where our prediction was a "NO" and the eventual output was also "NO".
(iii) FALSE POSITIVES: These are the cases where our prediction was a "YES" and the eventual output was also "NO".
(iv) FALSE NEGATIVES: These are the cases where our prediction was a "NO" and the eventual output was also "YES".

c. Area Under Curve

Area Under Curve (A.U.C.) is also a widely used metrics for evaluation. Area Under Curve (A.U.C.) is used majorly for binary classification problem. Area Under Curve (A.U.C.) of a classifier is equal to the probability that the said classifier would rank a positive example randomly chosen higher than negative example which is also randomly chosen.

d. F1 Score

The F1 Score is usually used to measure the accuracy of a test. The F1 Score is also the Harmonic Mean between Precision and Recall. The range for the F1 Score is binary [0, 1] and It tells us how precise our classifier is, i.e how many instances were classified correctly, as well as how wholesome it is as it does not miss a significant number of instances. The higher the F1 Score is, the better will be the performance of our model. F-measure is calculated as:

$$F\text{-}Measure = 2\frac{PR}{P+R}$$

e. Precision

This can be defined as the number or amount of correct positive results divided by the number or amount of positive results which are predicted by the classifier.

Precision is calculated as:

$$Precision(P) = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

f. Recall

This can be defined as the amount or number of correct positive results divided by the amount or number of all relevant samples i.e., all the samples that ought to have been identified as positive). Recall is calculated as:

$$Recall(R) = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

3.6 Evaluation

The loss for both the training and the validation data for model 1 and for model 2 is as shown in Figure 2 and Figure 3 respectively. As shown in the figures, model 1 quite over fitted and the validation loss was not quite stable like the training loss. Also, in Fig 3, there was a sudden spike in the validation loss at epoch 3. This is not so much of a surprise because of the imbalance in the dataset in favor of healthy birds. Validation loss is expected to stay below the training loss or at least stay the same level if there is no overfitting. Comparing the performances of both models, validation loss for model2 generally stays below the training loss (except for the spike at epoch 3), unlike the unstable model1 validation loss. It can be concluded that model2 performed better than model1 in terms of loss evaluation after the training.

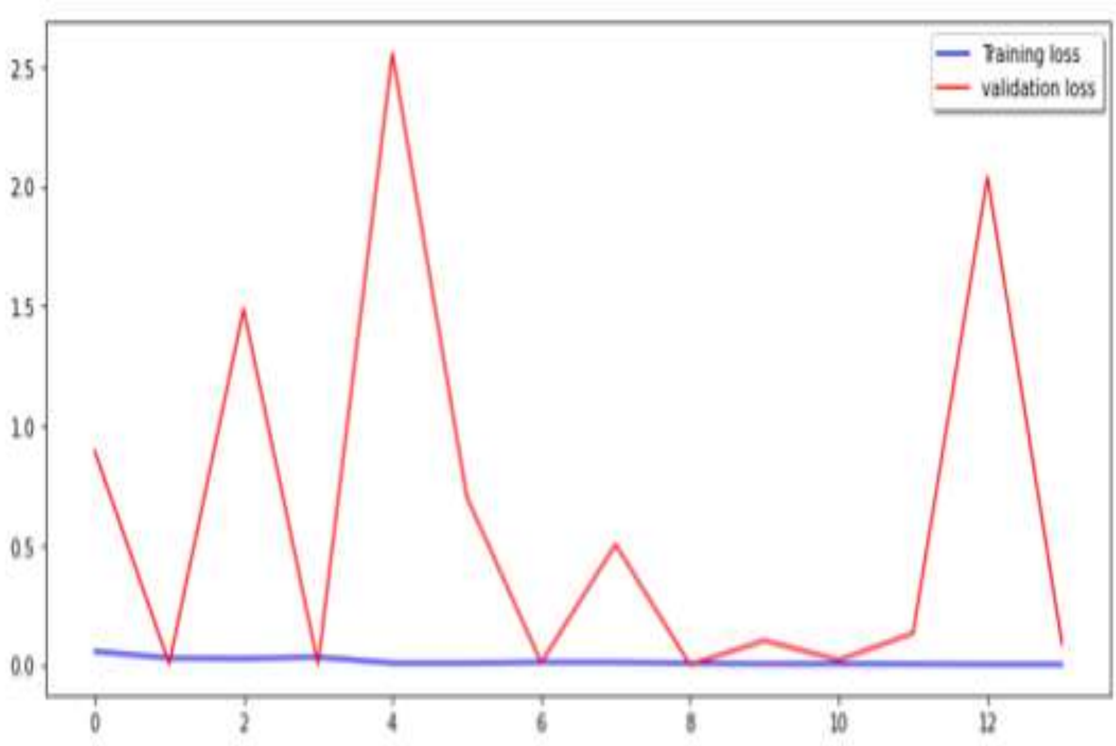

Figure 2. Loss of Model 1 Training

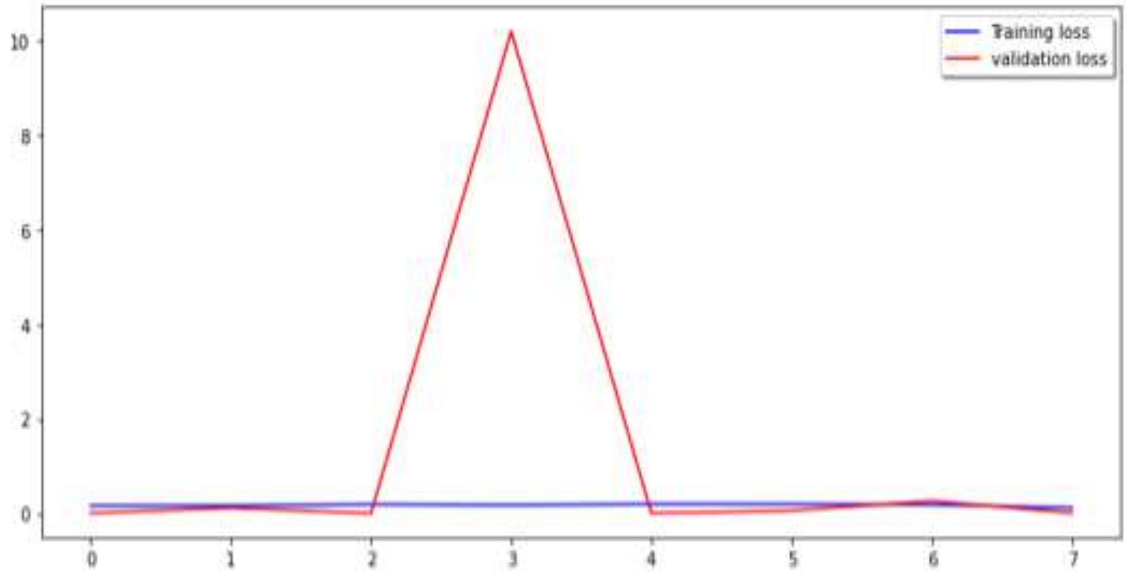

Figure 3. Loss of Model 2 Training

4. RESULTS AND DISCUSSION

This research has implemented a model that can be used for the Image Detection and Classification of Newcastle and Avian Flu Diseases Infected Poultry Using Machine Learning Techniques (Convolutional Neural Networks). To find the optimal parameters in our networks, the two optimization algorithms used are namely Adam and RMSprop optimizations. Using the same architecture, two models were trained using each optimization algorithms for each model respectively.

After training, the trained models' performances using the test set samples evaluated on the basis of their predictive accuracy, recall, precision, and f-score. From the Confusion matrix of Model 1, 10 sick birds out of the 146 birds were misclassified as healthy birds but all the healthy birds were correctly classified. More so, an accuracy of 93% was obtained. These misclassifications can be explained by attributing it to the imbalance in the training dataset in favor of the healthy birds.

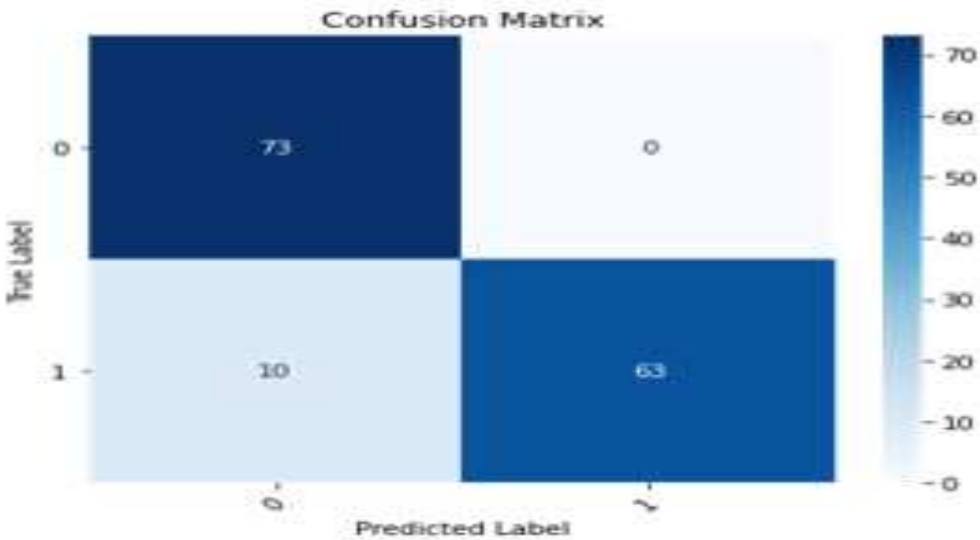

Figure 4. Model 1 Confusion Matrix of Test Set Sample Prediction.

```
PERFORMANCE EVALUATION (Model 1)
*********************************

          Classification Report
          ---------------------
          precision    recall  f1-score   support

       0       0.88      1.00      0.94        73
       1       1.00      0.86      0.93        73

accuracy                           0.93       146
macro avg      0.94      0.93      0.93       146
weighted avg   0.94      0.93      0.93       146

          Evaluation Metrics
          ------------------

          Accuracy:         0.932
          Recall:           0.863
          Precision:        1.0
          F1-Score:         0.926
          R2-Score:         0.726
```

Figure 5. Model 1 Classification Report and Performance Evaluation of Test Set Sample Prediction.

For model 2 on the other hand, only 5 sick birds out of the 146 birds were misclassified as healthy birds while all the healthy birds were correctly classified, giving a predictive accuracy of 97%. These misclassifications can also be traced to the imbalance in the training dataset in favor of the healthy birds. It is worthy of mention however that model 2 does better, almost twice as much as model 1 does, in correctly classifying the sick birds

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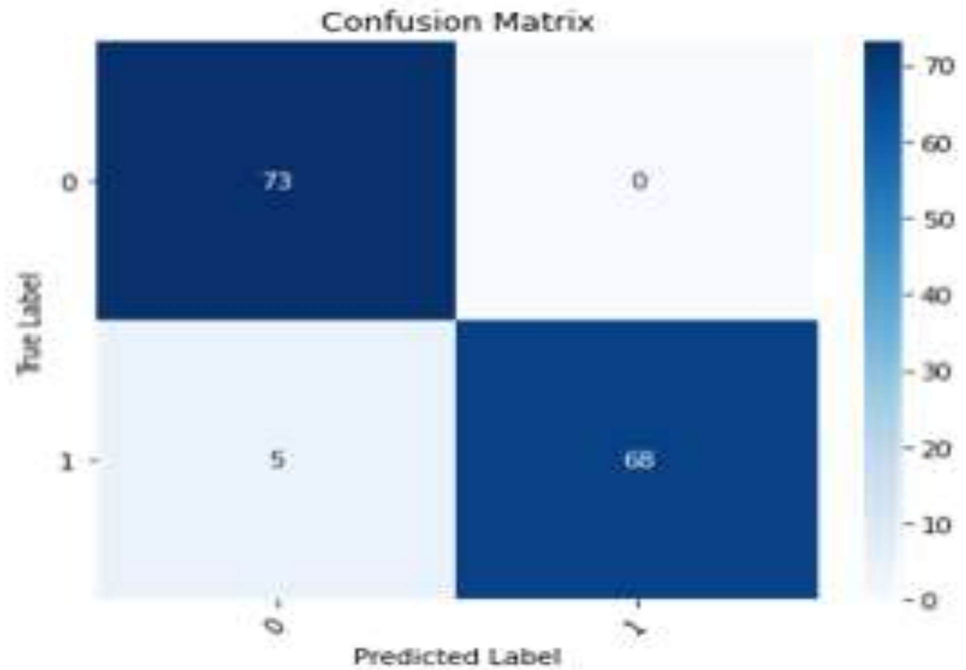

Figure 6. Model 2 Confusion Matrix of Test Set Sample Prediction

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PERFORMANCE EVALUATION (Model 2)
*********************************

                   Classification Report
                   ---------------------
              precision    recall  f1-score   support

           0       0.94      1.00      0.97        73
           1       1.00      0.93      0.96        73

    accuracy                           0.97       146
   macro avg       0.97      0.97      0.97       146
weighted avg       0.97      0.97      0.97       146

                   Evaluation Metrics
                   ------------------

                   Accuracy:        0.966
                   Recall:          0.932
                   Precision:       1.0
                   F1-Score:        0.965
                   R2-Score:        0.863
```

Figure 7. Model 2 Classification Report and Performance Evaluation of Test Set Sample Prediction

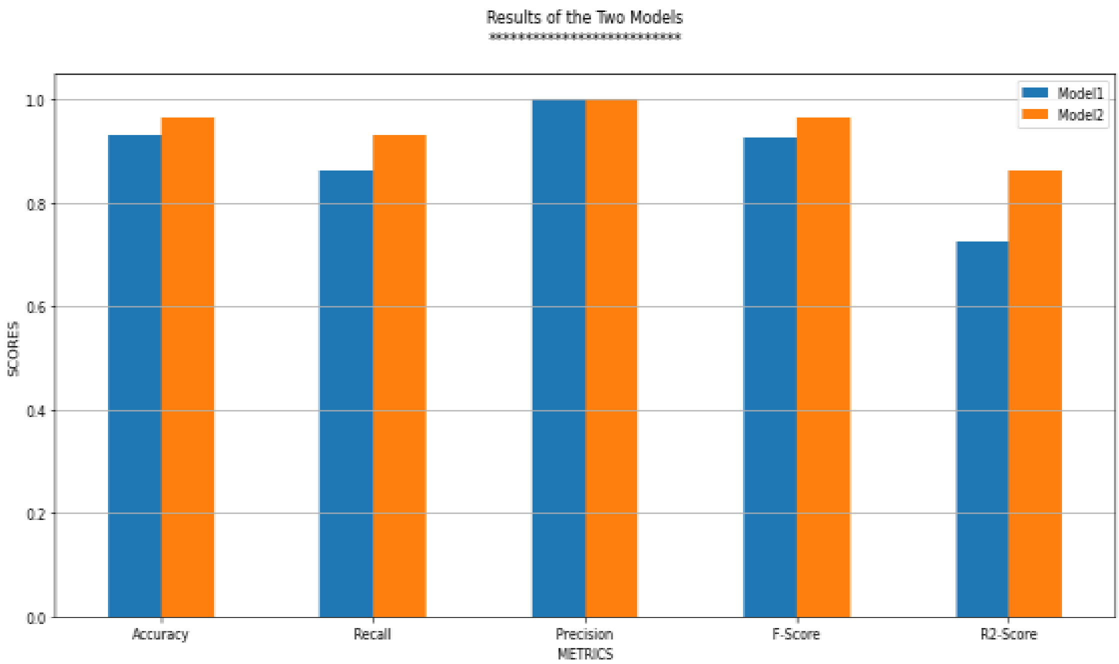

Figure 8. Comparative Evaluation of the models' performances

5. Conclusion

In conclusion, this research was able to develop two models for the Image Detection and Classification of Newcastle and Avian Flu Diseases Infected Poultry. During the course of this research in the early detection and classification of Newcastle and Avian Flu Diseased poultry, issues of imbalancing were encountered due to unavailability of sufficient dataset especially for the diseased poultry which should be a key criterion for future works. Further classification of sick birds into different disease categories can also be looked into.

This research work is recommended for the agricultural sector and researchers working in similar field. The project will aid in the early detection of Newcastle and avian flu diseases and will guard against the spread of the diseases.

References

[1] Patrick Gerland, Adrian E. Raftery, Hana Ševčíková, Nan Li1, Danan Gu1, Thomas Spoorenberg, Leontine Alkema, Bailey K. Fosdick, Jennifer Chunn, Nevena Lalic, Guiomar Bay, Thomas Buettner, Gerhard K. Heilig & John Wilmoth (2014). World population stabilization unlikely this century. *American Association for the Advancement of Science*, Vol. 346, Issue 6206, pp. 234-237, DOI: 10.1126/science.1257469.

[2] Alexander D.J. (2000). Newcastle disease and other avian paramyxovirus. *Revue scientifique et technique* (International Office of Epizootics) 19(2):443-62 DOI:10.20506/rst.19.2.1231

[3] Brown, V.R., Bevins, S.N. (2017). A review of virulent Newcastle disease viruses in the United States and the role of wild birds in viral persistence and spread. *Vet Res* 48, 68. https://doi.org/10.1186/s13567-017-0475-9

[4] M Sadeghi, A Banakar, M Khazaee & MR Soleimani (2015). An Intelligent Procedure for the Detection and Classification of Chickens Infected by Clostridium Perfringens Based on their Vocalization. *Brazilian Journal of Poultry Science*. Print version ISSN 1516-635XOn-line version ISSN 1806-9061. Rev. Bras. Cienc. Avic. vol.17 no.4 Campinas Oct./Dec. 2015. https://doi.org/10.1590/1516-635X1704537-544.

[5] Xiaolin Zhuang, Minna Bi, Jilei Guo, Siyu Wu, Tiemin Zhang (2018). Development of an early warning algorithm to detect sick broilers, *Computers and Electronics in Agriculture*, Volume 144, Pages 102-113, ISSN 0168-1699, https://doi.org/10.1016/j.compag.2017.11.032.

[6] Jintao Wang, Mingxia Shen, Longshen Liu, Yi Xu & Cedric Okinda (2019). Recognition and Classification of Broiler Droppings Based on Deep Convolutional Neural Network. *Journal of Sensors*, vol. 2019, Article ID 3823515, 10 pages, 2019. https://doi.org/10.1155/2019/3823515.

[7] Alice Mitchell (2015). New Technology Could Prevent Newcastle Disease Virus Replication. University of Georgia.

[8] A. Aydin, O. Cangar, S. E. Ozcan, C. Bahr, and D. Berckmans (2010). "Application of a fully automatic analysis tool to assess the activity of broiler chickens with different gait scores," *Computers and Electronics in Agriculture*, vol. 73, no. 2, pp. 194–199.

[9] Benjamin Graham (2014). Fractional Max-Pooling, version, v4 arXiv.org > cs>arXiv:1412.6071.

[10] Jake Astill, Rozita A. Dara, Evan D. G. Fraser & Shayan Sharif (2018). Detecting and Predicting Emerging Disease in Poultry with the Implementation of New Technologies and Big Data: A Focus on Avian Influenza Virus. Articles from Frontiers in Veterinary Science are provided here courtesy of Frontiers Media SA doi:10.3389/fvets.2018.00263.

[11] Jost Tobias Springenberg, Alexey Dosovitskiy, Thomas Brox & Martin Riedmiller (2015). Striving for Simplicity: The All Convolutional Net. (v1) arXiv.org > cs>arXiv:1412.6806.

[12] Kaiming He, Xiangyu Zhang, Shaoqing Ren & Jian Sun (2015). Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification. arXiv.org >cs >arXiv:1502.01852.

[13] Krizhevsky Alex, Sutskever, Ilya & Hinton, Geoffrey (2012). ImageNet Classification with Deep Convolutional Neural Networks. Neural Information Processing Systems. *Advances in Neural Information Processing Systems*, vol 25(2) DOI:10.1145/3065386.

[14] Srivastava Nitish, Hinton Geoffrey, Krizhevsky Alex, Sutskever Ilya & Salakhutdinov Ruslan (2014). Dropout: A Simple Way to Prevent Neural Networks from Overfitting. *Journal of Machine Learning Research,* vol 15(1):1929-1958.

[15] Hemalatha., Muruganand, S., & Maheswaran, R. (2014). Recognition of Poultry Disease in Real Time using Extreme Learning Machine. In *Proceedings of*

International Conference on Interdisciplinary Research in Engineering and Technology. 44-50 ISBN 978-81-929742-0-0

[16] Zhuang, Xiaolin & Zhang, Tiemin (2019). Detection of sick broilers by digital image processing and deep learning. *Biosystems Engineering*. 179. 106-116. 10.1016/j.biosystemseng.2019.01.003.

[17] Mbelwa, Hope & Mbelwa, Jimmy & Machuve, Dina (2021). Deep Convolutional Neural Network for Chicken Diseases Detection. *International Journal of Advanced Computer Science and Applications*. 12.10.14569/IJACSA.2021.0120295.

[18] Cedric Okinda, Innocent Nyalala, Tchalla Korohou, Celestine Okinda, Jintao Wang, Tracy Achieng, Patrick Wamalwa, Tai Mang, Mingxia Shen (2020). A review on computer vision systems in monitoring of poultry: *A welfare perspective*, *Artificial Intelligence in Agriculture*, Volume 4, Pages 184-208,ISSN 2589-7217, https://doi.org/10.1016/j.aiia.2020.09.002.