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Classification of Poultry Birds Based on Health State Using Convolutional Neural Network

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ABSTRACT

Monitoring the health of poultry birds is essential for ensuring the productivity and safety of poultry products. The conventional methods are often time-consuming, prone to errors, and ineffective at early disease detection. The drawbacks associated with the conventional methods often results to significant financial loss and increases disease spread within flocks, thereby impacting food productivity and safety. Addressing these challenges requires innovative solutions that improve the efficiency and accuracy of poultry health management. This study is part of a research work aimed at addressing the challenges of digitalized method of poultry bird's disease classification. To solved this, a classification of poultry birds based on health state using convolutional neural network model was developed, technique such as deep learning was used to analyzes diverse dataset of annotated images of birds with health conditions, for proper datasets classification, a convolutional neural network (CNN) was employed, the model as designed can accurately classify the health system of poultry birds from images, evaluate the performance of the developed model in terms of accuracy, precision, recall and F1 score. The model is embedded with a user-friendly interface and this was achieved through computer vision-based techniques, the interface enable users to upload images and result of different diseases as analyzed displayed

Keywords: Poultry, Health, Diseases, Model, Monitoring, Classification and Birds

1. INTRODUCTION

Agriculture remains a pivotal sector in Nigeria, crucial for job creation despite its reduced share in foreign exchange earnings. Approximately 65% of Nigerians depend on agriculture for their livelihood, contributing 34.8% to the national GDP and over 38% to non-oil foreign exchange earnings (Adene and Oguntade, 2006). Within this sector, poultry production stands out due to its potential to enhance food security and contribute to the UN Sustainable Development Goals (Adene and Oguntade, 2006). With a poultry population exceeding 200 million birds, Nigeria's poultry industry is the largest in Africa (Jatau *et al.*, 2016). Globally, poultry production is vital for meeting the increasing demand for nutritious animal protein, accounting for 24% of meat production in sub-Saharan Africa and 33% of Nigeria's total animal protein supply (Mottet and Tempo, 2017). Poultry farming is essential not only for food security and nutrition, but also for generating income, particularly in rural

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also for generating income, particularly in rural areas. Backyard poultry flocks have been instrumental in the substantial growth of Nigeria's poultry industry. A significant portion of the poultry found in the country's market originates from this grassroots segment of poultry farming (Adene and Oguntade, 2006). However, this sector lacks adequate safeguards for chicken health and biosecurity.

While local chicken rearing holds promise for boosting household incomes and nutritional security, however, the growth potential is being hampered by low productivity arising from disease outbreaks. This is often seen during dry season when there is a reduction and drawback in the supply chain of feeds (Joshi *et al*., 2021). Traditionally, farmers rely on expertise and experience to detect poultry diseases, often assessing bird health through faces. However, misdiagnoses and a scarcity of specialists can lead to significant flock losses. Among the most prevalent diseases affecting poultry are coccidiosis, Newcastle disease, and salmonellosis. Coccidiosis is a common disease caused by protozoal parasites of the *genus Eimeria,* which includes species such as *E. tenella, E. brunetti, and E. acervulina* (Blake et al., 2020). These parasites thrive in warm, humid conditions and can cause severe clinical signs such as poor growth, low egg production, and even death in severe cases. The disease also reduces feed conversion efficiency and exacerbates other health issues within the flock (Chapman, 2014). Newcastle Disease (ND) is a highly contagious viral disease caused by avian paramyxovirus type 1 (APMV-1). It affects a wide range of bird species, including chickens and turkeys, and is characterized by respiratory, nervous, and gastrointestinal symptoms (Munir, 2021). ND viruses are classified into five pathotypes: apathogenic, lentogenic, mesogenic, viscerotropic velogenic, and neurotropic velogenic, each varying in severity and clinical presentation. The most severe forms can cause high mortality and significant economic losses in poultry farms (OIE, 2021).

Salmonellosis is another major disease in poultry, caused by various strains of *Salmonella.* Young birds are particularly susceptible to pullorum disease, while adult birds can suffer from fowl typhoid, both of which are caused by *Salmonella gallinarum* (Andino and Hanning, 2015). The disease spreads through contaminated hatcheries, feed, and poultry houses, and can result in symptoms such as septicemia, inappetence, and mortality. Preventive measures include stringent biosecurity practices, vaccination, and proper hygiene and sanitation (García *et al*., 2019). Effective health management in poultry farming involves a comprehensive approach that addresses all factors impacting bird health, including environmental, social, and psychological aspects. This includes weather-proof housing, regular cleaning and disinfection, and robust biosecurity measures to prevent the introduction and spread of diseases. Vaccination programs also play a crucial role in mitigating the risk of contagious diseases (Bohrer, 2017; Flachowsky *et al*., 2017). Given the challenges posed by these diseases, there is a critical need for advanced health monitoring and disease detection systems in poultry farming. This research aims to address this

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need by employing deep learning algorithms in computer vision to quickly identify common poultry diseases from fecal images. By integrating technologies such as computer vision and deep learning, the goal is to provide a practical and seamless solution for the poultry industry. This innovation will streamline disease identification, enhance bird health, and increase overall poultry production. The adoption of such technologies allows the poultry sector to effectively address its challenges, reduce operational expenses, and deliver safer, higher-quality chicken and eggs to consumers.

By combining technological advancements with traditional approaches, this research aims to strengthen the resilience and efficacy of the poultry industry. The goal is to enhance disease detection capabilities while supporting sustainability in the face of evolving challenges. These advancements herald an era of data-driven decision-making and predictive analytics, enabling the anticipation of disease outbreaks, optimization of feed formulations, and fine-tuning of environmental conditions for optimal bird health. Empowering farmers with sensor integration and intelligent monitoring systems, alongside precision agriculture techniques, facilitates the development of tailored and effective strategies. Embracing these innovations not only ensures the financial viability of the poultry industry but also aligns with international sustainability goals by minimizing resource wastage and enhancing output efficiency. This shift towards ecological stewardship ensures industry prosperity while fostering a more environmentally conscious approach within the sector. Health classification models for poultry birds play a crucial role in monitoring and managing the health of these animals. Poultry birds, such as chickens, turkeys, and ducks, are prone to various diseases and health issues that can affect their well-being and productivity. An essential aspect of these models is identifying common diseases and health issues, including avian influenza, Newcastle disease, infectious bronchitis, and coccidiosis, as well as conditions like malnutrition, parasitic infestations, and injuries. By recognizing the signs and symptoms of these ailments, farmers and veterinarians can diagnose and treat affected birds more effectively. A critical task in poultry farming is classifying droppings based on characteristics like color, consistency, water content, and texture. Several studies have focused on classifying or segmenting droppings using image analysis (Okinda *et al*., 2019). However, significant variation exists in experimental conditions, ground truth establishment, and the number of classes used in these studies. The simplest classification task distinguishes between healthy and unhealthy droppings (Aziz and Othman, 2017). Given the importance of early disease detection, multi-class classification approaches are increasingly relevant. For instance, a recent study identified eight prevalent diseases, such as avian influenza and coccidiosis, that lead to diarrhea in chickens, highlighting distinctive visual dropping characteristics associated with each disease and the vulnerable time periods and risk levels (He *et al*., 2022). Visual differences in droppings affected by these

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diseases are noticeable when captured under controlled laboratory conditions with close-up shots. Some investigations take fecal images on a conveyor line, leading to different results under realistic conditions (Wang *et al*., 2019). These studies often classify droppings into several heuristic classes, including normal and abnormal fecal samples. For example, some authors classify droppings into "Coccidiosis," "Healthy," and "Salmonella," achieving high accuracy using fully connected CNN models (Mbelwa *et al*., 2021). Degu and Simegn (2023) proposed a four-class classification model, adding Newcastle Disease, utilizing YOLOv3 for object detection and ResNet50 for image classification, achieving a high accuracy. Various approaches can classify poultry droppings, including unsupervised and supervised machine learning techniques. Unsupervised approaches, such as clustering, do not require labeled data but rely on the data's intrinsic characteristics. However, achieving high accuracy requires highly distinctive features, making multi-class classification challenging. In contrast, supervised approaches use labeled data to train machine learning models for accurate classification. Substantial labeled data is essential for effective training. Deep learning architectures, in particular, show great potential due to their ability to learn complex data patterns and perform tasks like object detection, segmentation, and classification automatically.

Another critical component of a poultry health classification model is developing diagnostic criteria and algorithms for identifying and classifying health conditions (Wang *et al.*, 2019). This involves using clinical signs, laboratory tests, and imaging studies to assess individual birds' health status and determine appropriate actions. Standardizing the diagnostic process ensures consistent and accurate health assessments. Additionally, these models provide treatment and management recommendations, including medications, vaccines, dietary supplements, and other interventions to address specific health issues and promote overall well-being. Following these recommendations helps prevent disease spread, reduce mortality rates, and improve flock productivity (Nuru and Odetokun, 2011). Overall, a health classification model for poultry birds is a valuable tool for monitoring and managing bird health. By identifying common diseases and health issues, developing diagnostic criteria, and providing treatment recommendations, farmers and veterinarians can ensure their flocks' well-being and productivity. Implementing a comprehensive health classification model enhances the overall health and welfare of poultry birds, contributing to a more sustainable and profitable poultry industry. From the reviewed literatures, it was observed that approaches developed thus far are more of periodic review and poultry bird’s health status are often not predicted. To address the challenges, this work employed daily fecal synchronization using computer vision techniques.

2. Materials and Method

Building on the findings from the introduction, it is clear that poultry farmers urgently need a

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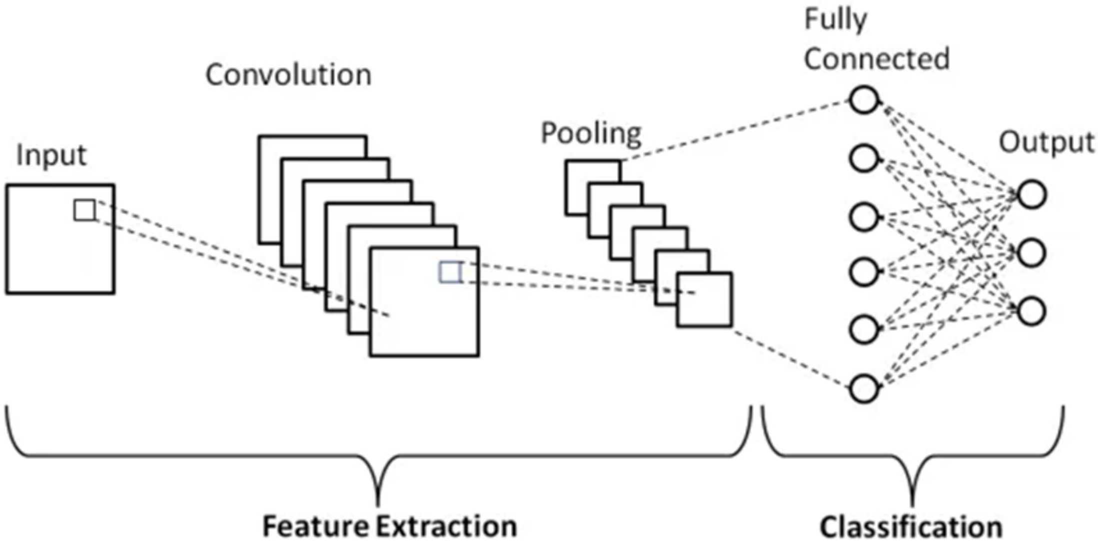

Figure 1: Convolutional Neural Network

straightforward, user-friendly, and cost-effective automated system to efficiently monitor and classify the health status of poultry birds. The substantial financial losses incurred by poultry farmers due to widespread diseases and infections underscore the critical importance of this study. This aspect provides a detailed overview of the methodology employed to achieve the study's objectives. The methodology detailed in this chapter leverages a diverse dataset of annotated images and a convolutional neural network (CNN) to ensure robust and accurate health classification as CNN is known for images extraction as revealed in Figure 1.

The model as proposed extract features from the images as captured and fed into the model via the input module and CNN being an embedded techniques use in artificial intelligence, it best serve the purpose of this work in extracting features required for analyzes within the model. Performance is evaluated using accuracy, precision, recall, and F1 score metrics. Additionally, a user-friendly interface and a mobile application was developed to provide farmers with accessible, real-time health monitoring tools. This approach aimed to offer a reliable, efficient, and practical solution to enhance poultry health management and productivity. The input requirements specify what the system requires in other to produce the required output. The input include:

I. Labeled life images of poultry birds specifying class

II. Dataset of existing poultry diseases

The output requirement specifies the kind of output required to be produced by the poultry health classification model. The model should produce the required output such as:

i. Healthy birds

ii. Coccidiosis diseases

iii. New castle disease

iv. Samonella disease

v. Unhealthy birds

2.1. Collection of Data Sets.

Gathering diverse and representative data sets is essential for training and testing the health

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classification model effectively. This involves sourcing annotated images and associated metadata that encompass various health conditions, symptoms, and physical appearances of poultry birds.

I. Collaboration with Veterinarians and Poultry Experts: During the requirement analysis phase, extensive collaboration with veterinarians and poultry experts was undertaken. These experts provided critical insights into the health indicators, symptoms, and visual cues associated with different poultry diseases. Their expertise ensured that the collected data was relevant and accurately represented the conditions necessary for effective health classification.

II. Data Collection Process: The data sets were collected from multiple sources to ensure diversity and representativeness. This included:

III. **Field Data Collection**: Images of poultry fecal samples were collected from two local farms, MAC Farms located at Uhogua Community and Ene Iwinosa Global Farms located at Okhunwun Community, both in Ovia North East L.G.A of Edo State. Over a period, a total of 2000 broilers were observed from day-old chicks to 10-week-old birds. Their droppings were captured at different intervals using a camera phone. These images were then labeled with the relevant health conditions identified by veterinarians.

IV. **Online Data Sources**: Additional annotated images were sourced from online databases and research repositories. This helped to supplement the field data, ensuring a robust and comprehensive data set.

2.2. Criteria for Selecting Data Sources

The selection of data sources was based on the following criteria:

1. **Relevance**: Data must be relevant to the health conditions being studied.
2. **Quality**: High-quality images that clearly depict the symptoms and conditions.
3. **Diversity**: A diverse range of samples to ensure the model can generalize across different conditions and environments.
4. **Expert Validation**: Data must be validated by veterinarians and poultry experts to ensure accuracy.

2.3. Data Preprocessing Steps

To ensure data quality and consistency, the following preprocessing steps were taken:

A. **Image Cleaning**: Removing any irrelevant or poor-quality images.

B. **Normalization**: Standardizing the image sizes and formats.

C. **Annotation**: Accurately labeling the images with the relevant health conditions.

D. **Augmentation**: Applying techniques such as rotation, scaling, and flipping to increase the variability of the dataset without changing the underlying health condition.

This phase is crucial for creating a high-quality, annotated dataset that accurately reflects the various health conditions of poultry birds. This data serves as the foundation for training and testing the deep learning model, directly impacting its accuracy and reliability.

3. The Architectural Design of Poultry Health Classification Model

Figure 2 shows the architecture of developed model for poultry health classification system. The design is embedded with different activities

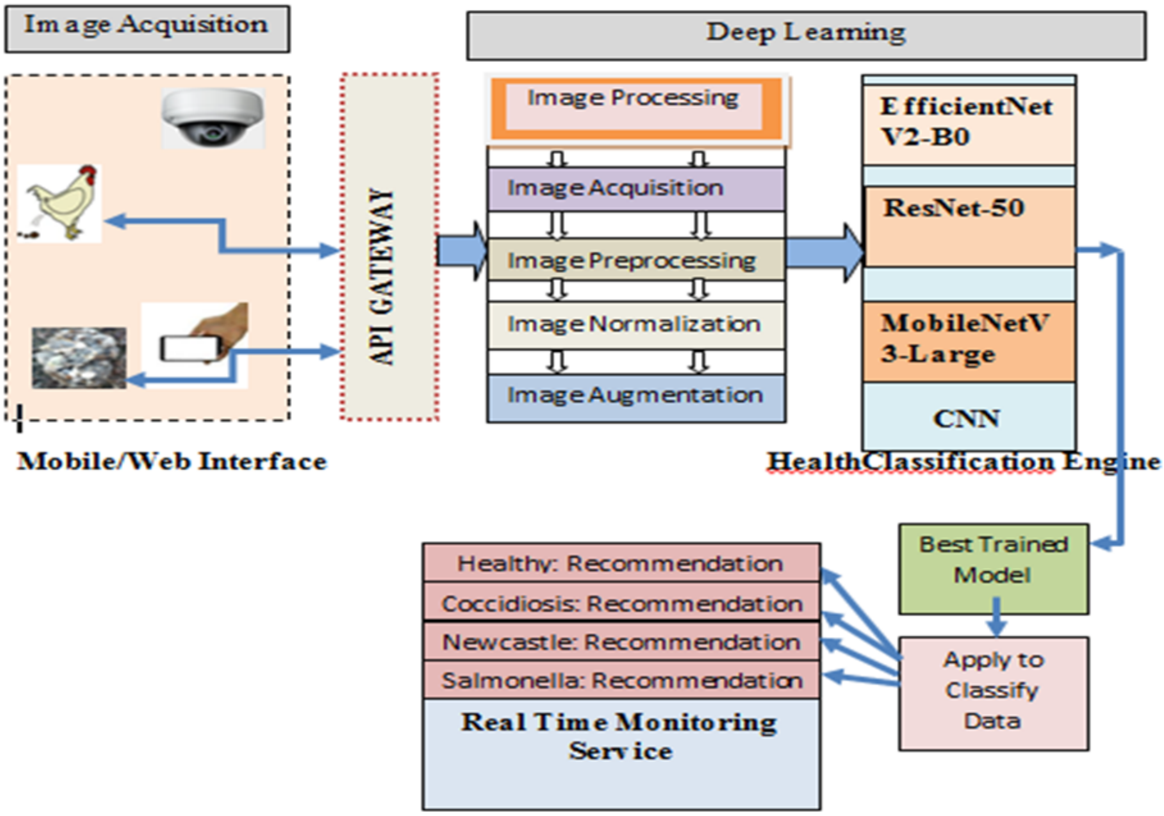

Figure 2. Architecture of a Poultry Health Classification Model

that take place for a particular poultry bird image to be classified on health status. On the received of the dataset, a pre-processing of the system will take place where the system preprocesses the poultry bird/fecal image. After which feature extraction is carried on the images. This give room for the features extracted from the image dataset to be trained, tested and classified using the deep learning algorithm. This leads to the classification of the image dataset as either "healthy, Newcastle disease, Coccidiosis or Salmonella disease" with their prospective recommendations for treatment. The achievement of Figure 2 follow TensorFlow structure and it is a powerful open -source library for numerical computation and large-scale machine learning. This method allows several data to be fed into the model. Keras, was used on the ensorFlow as the API, this offers the model a user-friendly interface.

EfficientNetV2-B0 is a CNN architecture known for its high accuracy and efficiency. At the image processing, it help to scale all images depth, width and resolution for optimal performance. The Efficient was used to concurrently ensure adequate comprehension of images scanned to the model through the guidelines and since, it is a B-style architecture of 6 convolutional blocks, it helped the model to set the width coefficient and depth coefficient to 1.0. .

ResNet-50 is architecture of CNN. It was employed to improve the model gradient flow during training and this was due to the disappearance of gradient during training. ResNet-50 consists of 50 layers, with batch normalization and ReLU activation preceding the convolution layers (v2 style). It is pre-trained on the ImageNet 2012 classification task.

MobileNetV3-Large: mobile and devices compatibility are largely handled by this CNN architecture, it does it through depth-wise separable convolutions. To solve deployment associated issue as it affect the mobile and other devices usage this method was adopted in other to achieve high accuracy with reduced computational costs. MobileNetV3-Large consists of 28 layers, with batch normalization and hard-swish activation applied after the convolution layers. It is pertained on the ImageNet 2012 classification task.

System Requirement Specification: The architecture of the proposed poultry health classification model has been designed, described and its components identified. To achieve this system as outlined in the architectural design, the next activity is to specify the design requirements needed to achieve the overall design goal. This is known as system design requirement specification. Here, the requirements in terms of all the expected output of the system, the inputs required to produce the required output, the processing steps that will be needed to transform the input into the desired outputs and the database design requirements were detailed. This will help give a better feeling when implementing the actual system.

Input Requirements: The input requirements specify what the system requires in other to produce the required output. The input requirement for our poultry health classification model should be the necessary input that will allow for the required output to be generated. These requirements include:

(i) Labeled life images of poultry birds specifying class

(ii) Dataset of existing poultry diseases

Output Requirements: The output requirement specifies the kind of output required to be produced by the poultry health classification model. The output for our proposed system should be able to produce the required output. This includes:

(i) Healthy birds

(ii) Coccidiosis diseases

(iii) New castle disease

(iv) Samonella disease

(v) Unhealthy birds

The algorithm below shows all the processing steps involved in training the system to identify and detect poultry bird health status. It uses the IF.. ELSE decision process in the algorithm and then marks the tested image as either 'Healthy', 'Newcastle disease', 'Coccidiosis', 'Salmonella' or 'Unhealthy'.

In the existing system that make use of this deep learning approach, once a poultry bird image is not found in the existing dataset, it just conclude that the image is unhealthy and then add it to the dataset as represented by the flowchart in Figure 3.

Poultry Health Classification Model Algorithm

Model Algorithm I

Input images
If images exist capture
Else capture from external
Then save
Enter user image of poultry birds: x;
Process x
Y = Select * from database
If image EQUAL x
If y
Print x. 'Corresponding diagnoses' ['Newcastle disease', 'coccidiosis', 'fowl pox', 'Salmonella']
else
Y = select * from database
If image EQUAL X
IF Y
Print x . 'is healthy'
else
Print x . 'is unhealthy'
End;

Model Algorithm II

Start
Enter
If login valid
Begin
Enter poultry bird image/feces to be checked in the input section
Process image for validation
Begin
Process data sets
If match
Begin
Process feature extraction
If feature is Healthy
Display "Healthy"
else display
If feature is Coccidiosis
Display "Coccidiosis"
Else display
If feature is New castle disease
Display "New castle disease"
else
If feature is Salmonella
Display "Salmonella"
else Display "Unhealthy"
stop;
End

Health Classification Model Flowchart

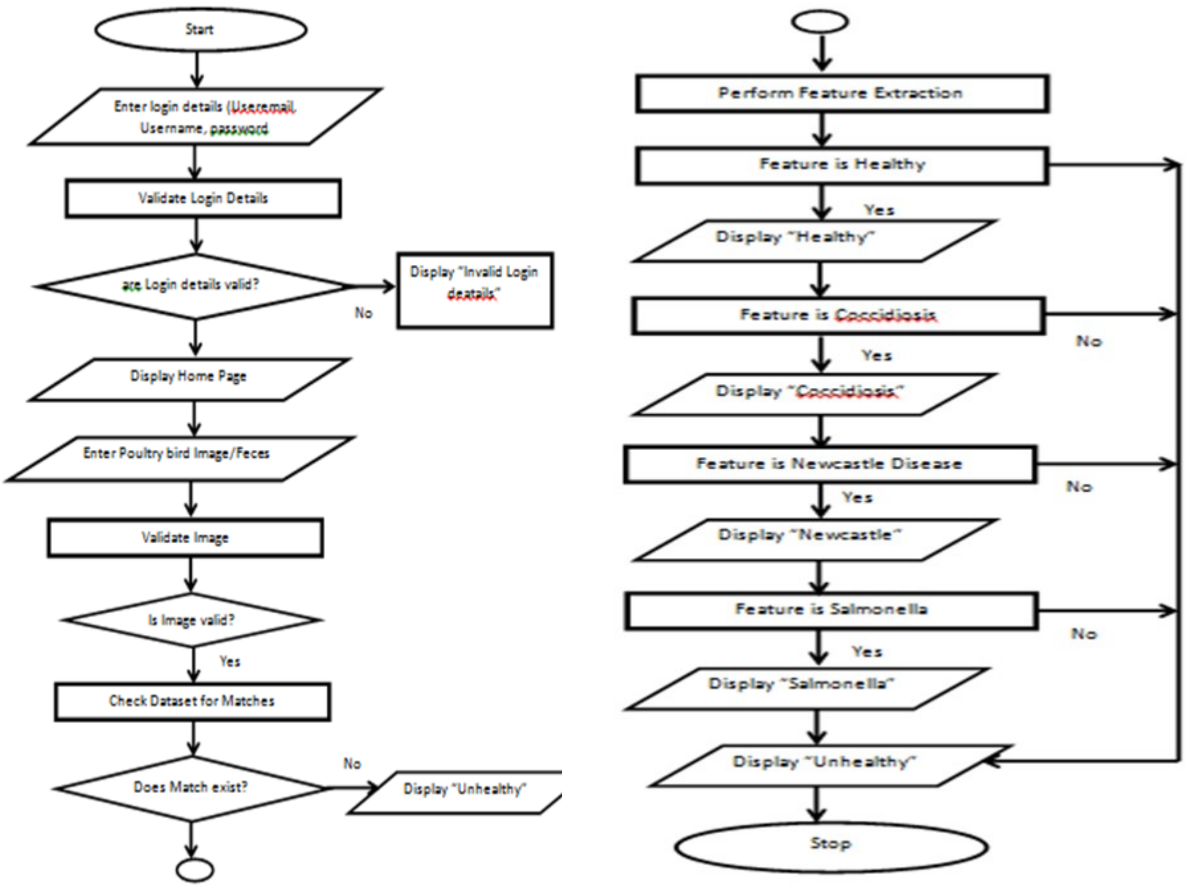

Figure 3: Poultry Health classification Model flowcharts

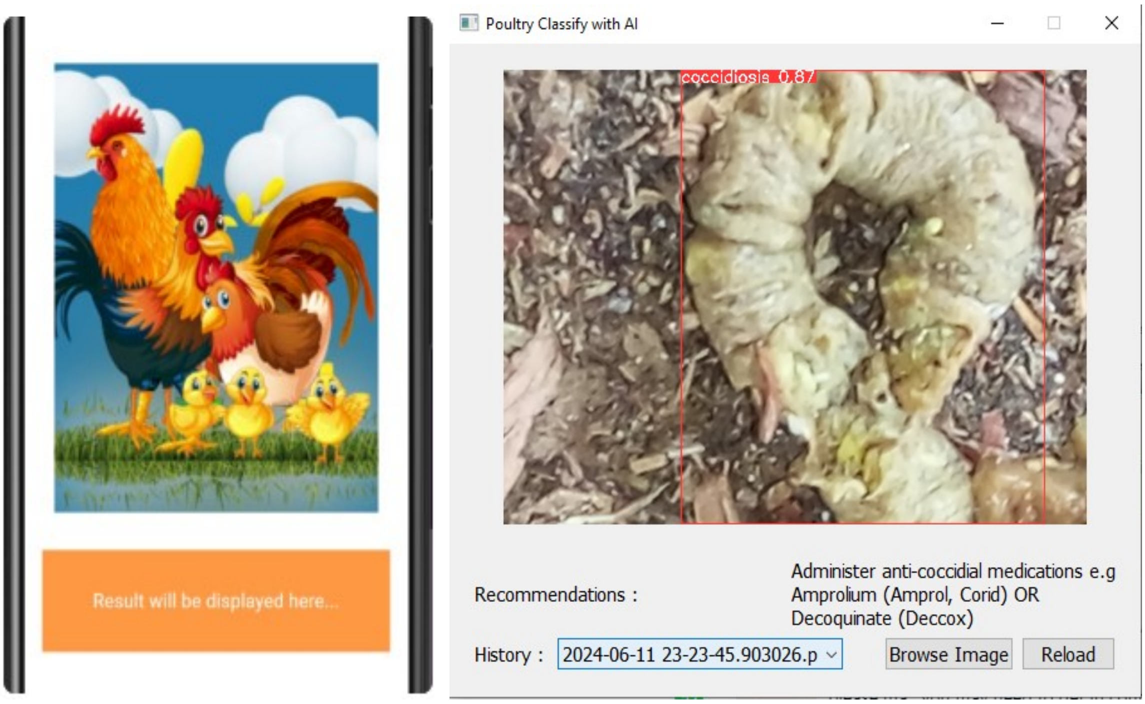

Figure 4: Output result of image analysis

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4. Results

In the result from the image analysis in Figure 4, shows that the results of the image analysis is displayed. i.e. the user can either snap the fecal images or upload the images from the gallery as screenshots of images saved from the camera view. The result indicates if the poultry birds are healthy or infected with Coccidiosis or Newcastle disease or Salmonella. If the images captured is unknown i.e neither healthy nor Coccidiosis nor Newcastle disease nor Salmonella, the results displays Unhealthy. The results also include recommendations for possible treatments.

The objective of this research is to create a health classification model for poultry birds utilizing a deep learning algorithm through a convolutional neural network approach. Previous chapters involved analyzing existing systems and gathering information to establish design specifications for the proposed system.

4.1. The Developed Health Classification Model for Poultry Birds

The developed poultry health classification app utilizes deep learning algorithms to analyze fecal images or images of poultry birds and classify their health status. The system is capable of identifying whether a bird is healthy, infected with Newcastle disease, coccidiosis, Salmonella, or falls under an unknown unhealthy category.

System Workflow

1. User Registration and Login

Registration: Users must register with their details to gain access.

Login: Users log in using their credentials.

2. Image Input:

Image Capture: Users can upload images of poultry birds or their fecal matter directly from the camera or gallery.

3. Health Classification:

Deep Learning Analysis: The system utilizes a CNN model to analyze the input images.

Classification: The system classifies the health status of the bird as healthy, Newcastle disease, coccidiosis, Salmonella, or unhealthy.

4. Result Output and Recommendations:

Display: The classification result is displayed on the user interface.

Recommendations: The system provides recommendations for treatment if the bird is classified as unhealthy.

5. Responsiveness:

Device Compatibility: The system is responsive and can be accessed on desktops, laptops, and Android mobile devices connected to the internet.

4.2. Evaluation of Model Performance

In this section, the assessment of the effectiveness of the developed poultry bird health classification model through rigorous performance evaluation metrics. The model's performance is crucial in determining its practical applicability and reliability in real-world scenarios. Accuracy, precision, recall, F1 score, and ROC-AUC plot were used to evaluate the performance of the models.

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The metrics were calculated from the model's confusion matrix based on TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) values as demonstrated in Equations (1–4). AUC-ROC plot was used to visualize how well the model can distinguish between classes.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (2)$$

$$\text{Precision} = \frac{TN}{TN + FP} \quad (3)$$

$$F\text{ (measure)} = \frac{2 * \text{Recall} * \text{precision}}{\text{Recall} + \text{precision}} \quad (4)$$

Table 1 and Figure 5 provides detailed statistics for each disease class, including precision, recall, F1-score, and support (number of true instances). The classification report table in Table 1 captures the other metrics (Recall, Precision, f1 score) of this model architecture on external (unseen data). The above plot in Figure 6 captures the progression of the loss and accuracy during the training of the EfficientNetV2-B0.

Left Plot: Accuracy vs. Validation Accuracy

X-axis: Represents the number of epochs. An epoch is one complete pass through the entire training dataset.

Y-axis: Represents the accuracy of the model. Accuracy is the ratio of correctly predicted instances to the total instances.

Blue Line (Accuracy)**:** Shows the training accuracy of the model over each epoch. Training accuracy measures how well the model is performing on the training data.

Red Line (Validation Accuracy): Shows the validation accuracy of the model over each epoch. Validation accuracy measures how well the model is performing on unseen validation data.

4.3. Right Plot: Loss vs. Validation Loss

X-axis: Represents the number of epochs.

Y-axis: Represents the loss of the model. Loss is a measure of how well the model's predictions match the actual target values. Lower loss indicates better performance.

Blue Line (Loss): Shows the training loss of the model over each epoch. Training loss measures how well the model is performing on the training data.

Red Line (Validation Loss): Shows the validation loss of the model over each epoch. Validation loss measures how well the model is performing on unseen validation data.

Generalization: This model demonstrates effective learning in the initial epochs, with both accuracy and loss showing significant improvements. Validation accuracy plateaus around 95%, indicating consistent performance on unseen data after the initial learning phase. It also shows that the model performs exceptionally well on the training set but does not generalize as well to the validation set.

Conclusion

The health classification of poultry birds is crucial for early detection and management of diseases such as coccidiosis, Newcastle disease, and salmonella. This research developed a robust health classification system using convolutional neural networks (CNNs), namely EfficientNet, MobileNet, and ResNet. These model as evaluated was based on performance metrics to determine the most effective

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Table 1: Classification Report for EfficientNetV2-B0

Column1	Precision	Recall	f1-score
Coccidiosis	0.99487179	0.984772	0.9897959
Healthy	0.90274841	1	0.9488889
Newcastle disease	0.88333333	0.757143	0.8153846
Salmonella	0.99088838	0.923567	0.956044
Accuracy	0.95668135	0.956681	0.9566814
macro avg	0.94296048	0.91637	0.9275283
weighted avg	0.95888019	0.956681	0.9563354

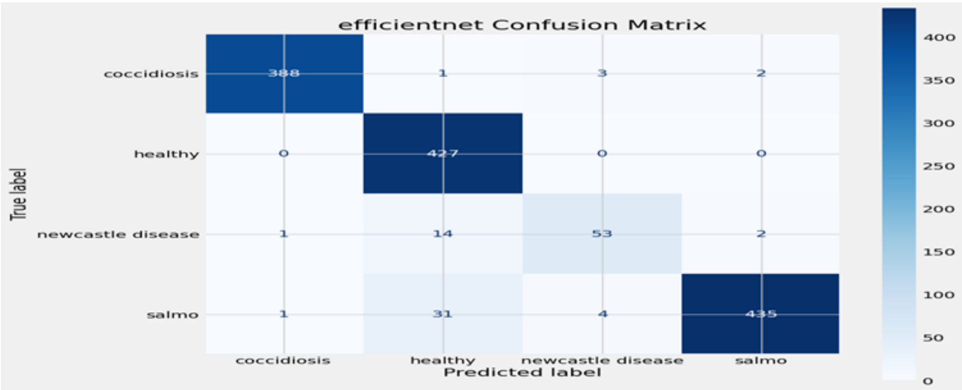

Figure 5: Confusion Matrix

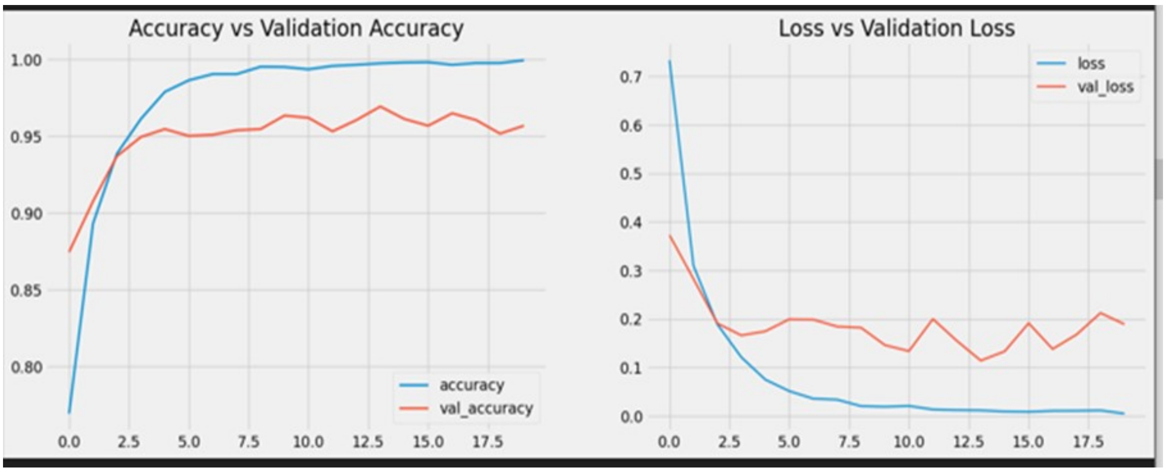

Figure 6: Machine learning Training and Validation Accuracy of EfficientNetV2-B0

classification accuracy. The daily classification of images fed to the model enable the designed system to be more proactive rather than reactive in handling the health status of poultry birds and this leads to increase in the production, healthy living of the birds which hitherto contributes immensely to the food bank of a nation as well as return of income on investment.

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