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Integrating Chicken Fecal Image Analysis with Machine Learning for Early Detection of Poultry Diseases in Developing Countries

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***Abstract*—the health and productivity of poultry farms are significantly impacted by the timely detection of diseases within chicken houses. Manual disease monitoring in poultry is laborious and prone to errors, underscoring the need for sustainable, efficient, reliable, and cost-effective farming practices. The adoption of advanced technologies, such as artificial intelligence (AI), is essential to address this need. Smart farming solutions, particularly machine learning, have proven to be effective predictive analytical tools for large volumes of data, finding applications in various domains including medicine, finance, and sports, and now increasingly in agriculture.**

Poultry diseases like Coccidiosis can lower chicken productivity if they are not detected early on. Machine learning, Deep learning algorithms can assist with the early identification of diseases. In this study, a Convolutional Neural Network based framework has been proposed to classify poultry diseases by distinguishing healthy and unhealthy fecal images. Unhealthy images can be a sign of poultry diseases. The Image Classification dataset was used to train a model, and it was discovered that it performed with an accuracy of 84.99%, 90.05% on the training set, testing set respectively. When the proposed network's performance was evaluated, it was discovered that the proposed model was unquestionably the best one for classifying chicken disease. This study explores the benefits of automated chicken disease detection as a function of smart farming in Zambia.

keywords: artificial intelligence, machine learning, early warning system, poultry health, smart farming.

I. INTRODUCTION

In recent years, poultry diseases have caused significant challenges for chicken farmers. These diseases not only result in economic losses but also pose risks to human health. Currently, veterinarians primarily diagnose poultry diseases by observing the behavior of chickens, examining physical signs such as combs, and analyzing fecal matter or listening to their vocalizations [1]. However, this manual method is often slow and prone to missing early signs of diseases [1].

Modern technological advancements offer more efficient solutions for monitoring chickens and detecting illnesses early. Technologies such as sound analysis, wearable devices, and cameras are used to monitor chicken behaviors. These devices track movements, like dust-bathing and pecking, and can even detect parasites on chickens' bodies [3].

Researchers have gathered extensive data on the behaviors of healthy and diseased chickens, which helps differentiate between the two states. This is vital for maintaining both poultry health and food safety [3]. Despite various efforts in disease prevention, including breeding disease-resistant chickens and using immune-enhancing products, disease outbreaks still occur, posing threats to the poultry industry and public health [4].

This paper investigates the application of machine learning techniques, particularly Convolutional Neural Networks (CNNs), for the automatic detection and classification of poultry diseases like Coccidiosis through fecal image analysis. By leveraging this approach, farmers can quickly identify diseased chickens and take timely action to prevent further spread and economic losses.

II. RELATED WORK

To supplement the findings and provide a broader understanding of the application of Machine Learning (ML) and Convolutional Neural Networks (CNNs) in poultry disease detection for chicken image analysis, several relevant studies were reviewed.

Degu and Simegn [2] explored advanced ML algorithms to identify and classify poultry diseases using fecal images.

Their work utilized YOLO-V3 for object detection and ResNet50 for image classification, achieving a mean average precision (mAP) of 87.48% and a classification accuracy of 98.7%, respectively. Despite these significant results, the system struggled to directly identify specific disease types, and the dataset included only three classes (Coccidiosis, Salmonella, and Healthy). Expanding the dataset could potentially improve the system's accuracy and robustness.

Wang et al. [5] developed an automated broiler digestive disease detector based on a deep CNN, which classified abnormal broiler droppings based on features such as shape, color, and water content. Although the results were promising, the study did not investigate the performance differences between Faster R-CNN and YOLO-V3, leaving a gap for further research. A comprehensive comparison of these two algorithms could be beneficial in future studies.

Machuve et al. [6] presented a deep learning model employing the MobileNetV2 architecture for diagnosing poultry diseases. This model achieved an F1 score above 75% across all classes. However, the study primarily classified images as healthy or unhealthy without addressing specific disease types, which limits its application in diagnosing particular diseases.

Srivastava and Pandey [6] built a CNN-based model that attained an impressive 93.23% accuracy on the test set, showing the efficacy of deep learning for classifying poultry diseases based on fecal images. Their findings reinforce the utility of CNNs in early disease detection within the poultry sector.

In a study by Hope Mbelwa et al. [8], the XceptionNet architecture outperformed other models for classifying chicken diseases based on droppings. Although the study claims superiority of XceptionNet, it lacks detailed information about the evaluation metrics (e.g., F1 score, precision), making it challenging to assess the model's complete performance.

Ghufran Ahmed et al. [3] explored multiple ML and deep learning techniques, including TabNet, Decision Tree, Random Forest, K-Nearest Neighbor, Support Vector Machine, and Logistic Regression for detecting chicken diseases. Their system achieved 97% accuracy in classifying healthy and sick chickens, demonstrating the potential of ensemble approaches. However, the use of an imbalanced dataset might have impacted the model's performance. The authors also proposed an IoT-based predictive service for real-time monitoring and early disease detection in poultry, which underscores the importance of integrating advanced technologies for poultry management.

Beyond image-based methods, Cedric Okinda et al. [10] proposed an AutoClassification System and a machine vision-based monitoring system to track broiler chickens and predict disease occurrences early. Despite the system's promise, it faced technical limitations related to lighting conditions, camera resolution, and image processing algorithms, which impacted its overall accuracy.

Another novel approach by Khushi Srivastava and Parth Pandey [9] utilized audio technology and deep learning through the Deep Poultry Vocalization Network (DPVN) to detect Newcastle disease. Although this approach focused on chicken vocalizations, it highlights the versatility of deep learning models (e.g., CNN, LSTM, GRU) in poultry disease detection tasks. The use of only twenty 15day-old SPF chickens limits the generalizability of the findings, but increasing the sample size could enhance the accuracy and reliability of future research.

III. MATERIALS AND METHODS

This section briefly discusses the materials and methods used to build a machine learning-based classification model for detecting poultry diseases through fecal image analysis.

A. Data Set

Two datasets were employed in this research: one sourced from Kaggle and another collected locally from poultry houses.

Kaggle Dataset:
Source: The dataset was downloaded from Kaggle.com.
Size: It comprises 800 labeled fecal images. Labels: Each image is labeled as either "Coccidiosis" or "Healthy."

Locally Collected Dataset:
Source: This dataset was collected from three local poultry houses in Zambia.
Size: It consists of 1,000 labeled fecal images.
Labels: Images were labeled as "Coccidiosis" or "Healthy."
Collection Method: High-resolution cameras were utilized to capture images from various sections of the poultry houses. Periodic sampling ensured diverse and representative images for analysis.

Preprocessing:
Image Augmentation: To increase dataset diversity and avoid overfitting, techniques such as rotation, flipping, and color adjustment were applied.
Resizing: All images were resized to a uniform resolution, either 224×224 RGB or 512×512 pixels, to ensure consistency and compatibility with the input requirements of the CNN architecture.

B. Materials

In this study,A Convolutional Neural Network (CNN) was designed specifically to detect and classify Coccidiosis in chickens using fecal images. The CNN architecture was constructed with multiple convolutional layers arranged sequentially. The model takes a 224×224 or 512×512 pixel RGB image as input and feeds it into the first convolutional layer, which performs feature extraction.

CNN Architecture:

The architecture involves several convolutional layers, followed by activation functions, pooling layers, and fully connected layers. The ReLU activation function was used in hidden layers, and the sigmoid function was employed in the output layer to classify images as either "Coccidiosis" or "Healthy." The Relu and Sigmoid function is defined as follows [11].

Each convolutional layer in our model employs filters with small receptive fields of 3×3 pixels, ensuring the extraction of fine-grained features from the input images. Following each convolutional layer, a max pooling layer is applied over a 2×2 pixel window to down-sample the feature maps, reducing the computational load while retaining essential features. This combination of convolution and max-pooling layers forms a single block, which is repeatedly applied throughout the network with an increasing depth of filters.

The depth of the filters across the convolutional blocks is set to 32, 64, 64, 128, 128, 256, 256, and 512, allowing the model to capture complex patterns in the images. To maintain the spatial dimensions of the feature maps, the same padding is applied in all convolutional layers. The ReLU activation function is used after each convolutional layer to introduce nonlinearity, enhancing the model's ability to learn intricate patterns.

Given the binary nature of our classification problem (Coccidiosis vs. Healthy), a binary cross-entropy loss function was chosen, which is specifically designed for binary classification tasks. The output layer of the network consists of a single node with a sigmoid activation function. This function outputs a probability between 0 and 1, representing the likelihood that the input image belongs to the Coccidiosis class, facilitating the final classification decision.

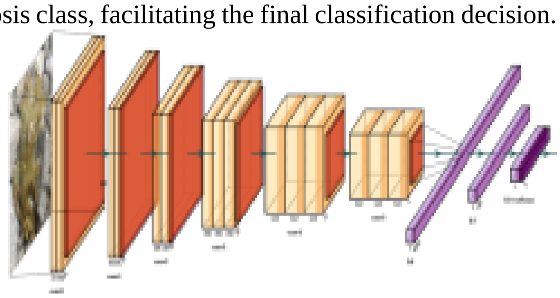

Fig. 1. Configuration of Fully Connected CNN Proposed Model

i. Feature Selection and Extraction

Feature Selection:

In image classification, feature selection refers to identifying the most relevant parts of an image that contribute to the classification task. Convolutional Neural Networks (CNNs) inherently perform feature selection during their convolutional and pooling layers by learning hierarchical representations of the input images. In the context of chicken fecal image analysis, these features could include textures, patterns, and colors indicative of disease conditions such as Coccidiosis.

Feature Extraction:

Convolutional Layers: These layers apply filters to the input images, detecting features such as edges, textures, and patterns that are important for distinguishing between healthy and diseased chicken fecal images. Each filter produces a feature map, highlighting specific aspects of the image relevant to the classification of Coccidiosis or Healthy conditions.

FullyConnectedLayers:

After feature extraction through convolution and pooling, fully connected layers integrate the extracted features to perform the final classification. The final output layer utilizes a sigmoid activation function to produce probability scores for each class (Coccidiosis or Healthy), ensuring accurate disease identification.

ii. DATA PREPARATIONS

The image_dataset_from_directory function is used to load and preprocess the images. Each image is resized to 224x224 pixels to ensure uniform input dimensions. Additionally, the images are normalized by scaling pixel values to a range of 0 to 1, which helps improve model training by ensuring that all pixel intensities fall within a consistent range.

iii. TRAINING THE MODEL

The model is compiled using the Adam optimizer, known for its efficiency and adaptive learning rates. For the loss function, binary cross-entropy is used, which is appropriate for the binary classification problem of distinguishing between Coccidiosis and Healthy conditions.

The training process involves 20 epochs, where 60% of the Kaggle dataset and 80% of the locally collected dataset are utilized for training. The remaining portions of the datasets are reserved for validation, allowing the model to be evaluated on unseen data and ensuring that it generalizes well to new samples.

(a) (b)

Fig. 2. Sample Images from the Fecal Image Dataset. (a) Coccidiosis (b) Health

Fig. 3 Above. Sample Healthy Images from Fecal Images Dataset.

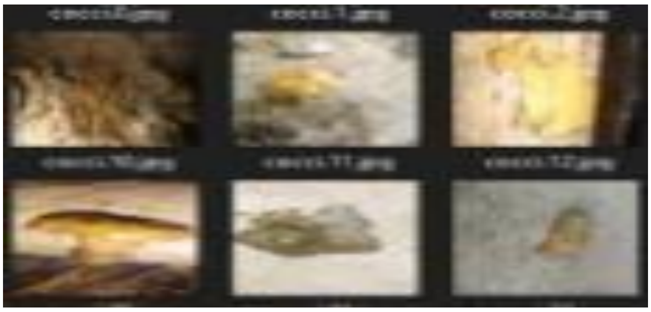

Fig. 4 Above. Sample Coccidiosis Images from Fecal Images Dataset.

IV. EVALUATING THE MODEL AND MAKING PREDICTIONS

The CNN model was evaluated using image analysis for poultry disease detection. The evaluation was conducted using two approaches:

1. Trained on Kaggle image dataset: The model was trained on images from the Kaggle dataset and tested on the locally collected image dataset.
2. Trained on local image dataset: The model was trained on 80% of the locally collected images and evaluated on the remaining 20%.

The goal was to assess the model's ability to accurately analyze chicken fecal images and classify them as either healthy or diseased. Below is the code used to evaluate the model, make predictions, and calculate accuracy based on image data.

IV. EXPERIMENTS

This study evaluates the performance of a machine learning-based system that integrates chicken fecal image analysis for early detection of poultry diseases in Zambia. The experiments were conducted using two distinct datasets: the Kaggle dataset and a locally collected dataset of chicken fecal images.

1. **First Experiment**: The CNN model was initially trained using the Kaggle dataset, which contains images related to poultry health, and tested on the locally collected dataset. This experiment aimed to assess the model's ability to generalize across different datasets and accurately detect and classify diseases from local chicken fecal images.
2. **Second Experiment**: The CNN model was then trained using the locally collected dataset, which was split into 80% for training and 20% for testing. This experiment tested the model's performance when using locally relevant data, ensuring the model's applicability in detecting poultry diseases in Zambian chicken farms.
3.

V. RESULTS AND DISCUSSION

This section presents the results and discusses the findings obtained from the experiments conducted using two different datasets: the Kaggle dataset and the locally collected dataset.

Table 1: Accuracy Scores

Experiment	Training Dataset	Testing Dataset	Accuracy
1	Kaggle Dataset (60%)	Local Dataset (40%)	84.99%
2	Local Dataset (80%)	Local Dataset (20%)	90.05%

1. Evaluation with Locally Collected Dataset
The model, initially trained with the Kaggle dataset, was evaluated using the entire locally collected dataset to assess its generalization performance on new, unseen data.
2. Evaluation with Split Locally Collected Dataset The model was trained with 80% of the locally collected dataset and evaluated with the remaining 20% to measure its performance on a split of the same data source.

DISCUSSION

The results from the experiments using both the Kaggle and locally collected datasets demonstrate the performance of the CNN model in classifying poultry diseases through **chicken fecal image analysis**.

Experiment 1: Training with Kaggle Dataset and Testing with Local Dataset

In the first experiment, the CNN model was trained on chicken fecal images from the Kaggle dataset, using 60% of the dataset for training and validating with 40%. When tested on the locally collected fecal images, the model achieved an accuracy of 84.99%**.** While this demonstrates the model's ability to detect diseases based on fecal image analysis, the lower accuracy compared to the locally trained model suggests that images from the Kaggle dataset may differ from local images in terms of resolution, lighting, or even the specific disease markers present in Zambian poultry feces. These factors could have slightly hindered the model's ability to generalize across different datasets. Nevertheless, the model performed well, showing that fecal image analysis can be a powerful tool for early disease detection, even with external datasets.

Experiment 2: Training with Local Dataset (80%) and Testing with Local Dataset (20%)
In this experiment, the CNN model was trained and tested entirely on locally collected chicken fecal images, with 80% used for training and 20% for testing. The model's accuracy improved to **90.05%**, highlighting the effectiveness of training on images that are more representative of the local poultry environment. The locally collected fecal images better capture the specific visual indicators of diseases like Coccidiosis, which might vary based on local environmental factors, feed, and disease manifestations..
These findings underscore the importance of utilizing local datasets for accurate fecal image analysis, as the model is better equipped to detect and classify poultry diseases when trained on images that reflect the actual conditions and disease patterns present in the region.

Key Observations from graphs above

Initial Training Phase (Epochs 010): Both training and validation accuracy increase rapidly, indicating that the model is learning from the data. The training accuracy increases more steadily than the validation accuracy.
Post Fine-Tuning (Epochs 10-20): After fine Tuning starts, as indicated by the green line, both training and validation accuracy show further improvement. The validation accuracy experiences some fluctuations but eventually trends upwards, suggesting that fine-tuning helped the model generalize better to new data.
analysis in enhancing early detection of diseases like Coccidiosis.
Future research could focus on expanding the dataset to include a wider variety of disease types and conditions, as well as optimizing the model's architecture to improve its robustness and real-world applicability in diverse farming settings.

CONCLUSION AND RECOMMENDATIONS

The experiments demonstrate the potential of **chicken fecal image analysis** using convolutional neural networks (CNNs) for automated disease detection in poultry farming. The higher accuracy achieved with the locally collected dataset emphasizes the importance of training models on locally relevant data, which better captures the specific visual characteristics and nuances of poultry diseases in a particular environment, such as Zambia. This highlights the effectiveness of region-specific fecal image

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