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Automating Poultry Disease Detection using Deep Learning

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Abstract

Poultry farming plays a vital role in global food production but the emerging threat of diseases poses significant challenges to both sustainability and food security. In particular, this research study investigates the integration of deep learning techniques to automate the detection of four major poultry diseases—Avian Influenza, Coccidiosis, Newcastle Disease, and Gumboro Disease—from faecal samples. The proposed methodology involves collecting diverse faecal samples, pre-processing the data, and developing a Convolutional Neural Network (CNN) architecture. The CNN layered architecture is designed to extract hierarchical features and learn complex patterns associated with each disease. Through the integration of activation function, Rectified Linear Units (ReLU), the network incorporates non-linearity, enhancing its ability to detect the disease-related features. The faecal samples undergo image enhancement, normalization, and segmentation to ensure suitability for the deep learning model. The performance of the proposed model is evaluated using the performance metrics and achieved an overall accuracy of 98.82% on the training set, 93.22% on the testing set, and 96.65% on the validation set., precision, recall and F1-Score. This research study contributes to the advancement of automated disease detection, offering a potential solution to mitigate the impact of poultry diseases and enhance overall food safety.

Keywords: Convolutional Neural Network (CNN), Poultry Disease Detection, Faecal Images, Deep Learning

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1. Introduction

Poultry farming stands as a cornerstone of global agriculture, playing a pivotal role in meeting the rising demand for high-quality protein. The industry encompasses the rearing of domestic fowls such as chickens, turkeys, ducks, and geese, contributing significantly to the world's food supply. Poultry not only provides a vital source of meat and eggs but also serves as a crucial economic driver, supporting livelihoods and fostering rural development. However, the poultry sector faces persistent challenges, with diseases posing a constant threat to the health and productivity of flocks [1]. Timely detection and effective management of poultry diseases are essential for maintaining the economic sustainability of the industry and ensuring food security. Among the various methods available for disease detection, automating the process from faecal samples using advanced technologies like deep learning holds immense potential [2].

Faecal samples provide valuable insights into the health of poultry flocks, offering a non-invasive and easily accessible source of diagnostic information [3]. By automating the disease detection process from faecal samples, the poultry industry stands to benefit from increased efficiency, reduced response times, and enhanced accuracy in identifying potential health threats. In light of the intricate nature of poultry diseases and the sheer scale of the industry, leveraging cutting-edge technologies has become imperative [4].

Deep learning, a subset of artificial intelligence, presents an innovative approach to disease detection. By training neural networks to recognize complex patterns and subtle indicators of diseases from faecal samples, we can establish a robust and efficient system for early diagnosis. This research focuses on automating the detection of four major poultry diseases—Avian Influenza, Coccidiosis, Newcastle disease, and Gumboro disease—through the analysis of faecal samples [5]. Leveraging Convolutional Neural Networks (CNNs), a subset of deep learning, the study aims to harness the power of machine learning algorithms to identify intricate patterns associated with each disease. The integration of activation functions, such as Rectified Linear Units (ReLU), enhances the network's ability to learn and recognize complex features [6].

To address these challenges, this research proposes a deep learning-based algorithm for the classification of poultry diseases. Utilizing a publicly available dataset with diverse disease classifications, the algorithm focuses on the categorization of four different diseases viz. Avian Influenza, Coccidiosis, Newcastle disease, and Gumboro disease. The dataset comprises images of poultry faeces, and augmentation strategies have been employed to ensure balanced training across classes [7].

The proposed methodology encompasses the collection of diverse faecal samples, pre-processing techniques to optimize the input data, and the development of a specialized CNN architecture. This model is designed to learn hierarchical features from images, providing a robust foundation for automated disease detection. The significance of this research lies in its potential to offer a swift and accurate means of identifying poultry diseases, thereby facilitating proactive measures to curb their impact on the poultry industry. As we delve into the details of the methodology and results, the broader implications of integrating deep learning into poultry disease detection systems become evident.

2. Literature Review

Poultry farming stands as a critical component of global food production, providing a primary source of protein through the production of meat and eggs. However, the poultry industry faces persistent challenges due to the prevalence of diseases that not only threaten economic sustainability but also pose risks to global food security [8]. As a response to these challenges, there has been a growing interest in leveraging advanced technologies, particularly deep learning, to automate the detection of poultry diseases, specifically from faecal samples.

The intersection of technology and agriculture has seen a surge in research exploring the application of deep learning techniques for disease detection in poultry. Recognizing the need for rapid and accurate identification of diseases, various studies have explored the integration of machine learning and computer vision methods to analyze diverse datasets, including faecal samples. The work of [9] focused on the use of machine learning algorithms for the automated diagnosis of poultry diseases, highlighting the potential for early detection and proactive management.

The importance of non-invasive methods for disease detection, such as analyzing faecal samples, has been underscored in several studies. [10] emphasized the value of faecal samples as a diagnostic medium, citing their accessibility and the rich information they provide about the health of poultry flocks. These studies form the foundation for the current research, acknowledging the significance of faecal samples in disease detection.

Deep learning, particularly Convolutional Neural Networks (CNNs), has demonstrated remarkable success in various image-based applications, including medical image analysis and disease detection. In the field of agriculture, [11] utilized CNNs for the identification of plant diseases from images, showcasing the potential of deep learning in automating disease diagnosis. The transferability of such techniques to the domain of poultry health underscores the relevance and promise of this research.

The proposed methodology aligns with the broader trend in the scientific community towards integrating deep learning techniques for automated disease detection. Studies such as [12] have successfully applied deep learning to detect specific poultry diseases, paving the way for more comprehensive approaches that encompass multiple diseases, as proposed in the current research.

Activation functions, such as Rectified Linear Units (ReLU), have been widely acknowledged in deep learning for enhancing the learning capabilities of neural networks. [13] explored the impact of activation functions on the performance of deep learning models in faecal image analysis, providing insights into their role in discerning subtle disease-related features. This research draws inspiration from such findings, incorporating ReLU activation functions to optimize the deep learning model's ability to identify complex patterns associated with poultry diseases.

The existing research literature underscores the importance of developing automated systems for poultry disease detection. By leveraging deep learning techniques, particularly CNNs, and integrating activation functions to enhance model capabilities, this research study aims to contribute to designing a robust and efficient solution for timely disease detection in poultry farming.

3. Proposed Methodology

3.1 Dataset Description

The dataset collected for this research study represent a diverse and comprehensive collection of faecal samples obtained from poultry flocks. The samples are sourced from various geographical locations and different poultry farming environments to ensure the model's robustness and adaptability across diverse scenarios.

3.2 Sample Collection

The faecal samples are collected from poultry farms with varying sizes and management practices to capture the heterogeneity of real-world conditions. Samples are sourced from poultry flocks exhibiting diverse health conditions, including those affected by Avian Influenza, Coccidiosis, Newcastle Disease, and Gumboro Disease, as well as samples from healthy flocks for comparison. A total of 2800 images were collected and trained. The dataset encompasses a wide range of faecal samples, considering variations in color, texture, and overall appearance. Samples include those from different poultry species, ages, and breeds, acknowledging the diversity in poultry populations.

3.3 Data Pre-Processing

Image enhancement techniques are applied to ensure optimal quality and consistency across the dataset. Normalization procedures are implemented to standardize the pixel values, facilitating effective training of the deep learning model. Segmentation is performed to isolate regions of interest within the faecal samples, emphasizing the areas relevant to disease detection.

3.4 Labeling

Each sample is meticulously labeled to indicate the presence or absence of the four major poultry diseases: Avian Influenza, Coccidiosis, Newcastle Disease, and Gumboro Disease. Expert veterinarians and domain specialists contribute to the accurate labeling of the dataset, ensuring reliability in disease annotations.

3.5 Dataset Description

The dataset is sufficiently large to facilitate effective training of the Convolutional Neural Network (CNN) architecture proposed in the study. It is divided into training, validation, and testing sets to evaluate the model's performance comprehensively.

Table -1 shows the details about the samples of the dataset used in training, validating, and testing

Table 1. Dataset Description

Class	Training set	Validation set	Testing set
Avian Influenza	784	224	112
Coccidiosis	784	224	112
Newcastle Disease	784	224	112
Gumboro Disease	784	224	112

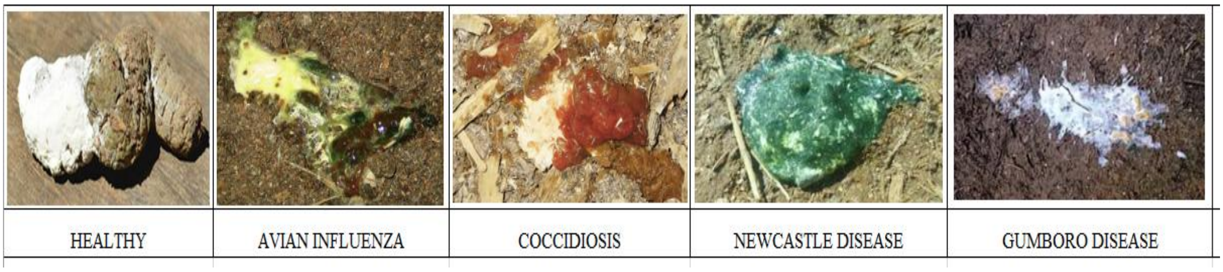

Figure 1. Sample Images for Each Class

3.6 Proposed Block Diagram

This simplified block diagram represents the flow of information through the various stages of the poultry disease detection system. Input faecal samples undergo data pre-processing, followed by convolutional layers in a neural network. The network's output is then flattened, processed through fully connected dense layers, and finally classified into disease classes in the output layer. The resulting prediction is used to generate the detection result. Figure 2 depicts the block diagram of the proposed model.

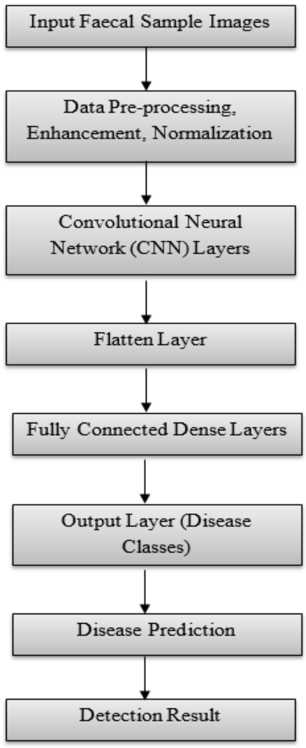

Figure 2. Block Diagram

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 64, 64, 32)	896
activation_1 (Activation)	(None, 64, 64, 32)	0
max_pooling2d_1 (MaxPooling	(None, 32, 32, 32)	0
conv2d_2 (Conv2D)	(None, 32, 32, 64)	18496
activation_2 (Activation)	(None, 32, 32, 64)	0
max_pooling2d_2 (MaxPooling	(None, 16, 16, 64)	0
flatten_1 (Flatten)	(None, 16384)	0
dense_1 (Dense)	(None, 512)	8389120
activation_3 (Activation)	(None, 512)	0
dropout_1 (Dropout)	(None, 512)	0
dense_2 (Dense)	(None, 5)	2565
activation_4 (Activation)	(None, 5)	0

Total params: 8,410,077
Trainable params: 8,410,077
Non-trainable params: 0

Figure 3. Proposed CNN Layer Architecture

Conv2D Layers: These convolutional layers are responsible for learning hierarchical features from input images. The number of filters increases in deeper layers to capture more complex patterns related to diseases.

MaxPooling2D Layers: After each convolutional layer, max-pooling layers reduce spatial dimensions, retaining the most important features while discarding less relevant information.

Activation Layers: These layers apply the Rectified Linear Unit activation function element-wise to introduce non-linearity into the model. ReLU is commonly used in CNNs to allow the model to learn complex patterns.

ReLU Activation Equation is given as:

$$RELU(m) = \begin{cases} 0, & m \leq 0 \\ m, & m > 0 \end{cases}$$

Flatten layer: The flatten layer converts the 3D output into a 1D vector, preparing the data for fully connected layers.

Softmax Activation: While it's not explicitly shown in the architecture, the final dense layer is usually followed by a softmax activation function, which converts the network's output into probability distributions over the classes. The Sofmax activation function is denoted as:

$$Softmax\ (Z_i) = \frac{\exp(Z_i)}{\sum \exp(Z_i)}$$

Dense layers: Fully connected layers use the flattened features to make decisions about the presence of diseases. The last dense layer has as many neurons as there are classes (4 in this case) with a softmax activation function to produce class probabilities.

Dropout layer: Dropout is included to prevent overfitting by randomly setting a fraction of input units to zero during training.

4. Experimental Results and Discussion

The proposed system's technical specifications include 8 GB SDRAM, 10^{th} Gen, Intel i3 core processor and Windows 10 as OS for training the proposed framework. Further, Intel

4GB graphics card is used. In the training CNN model, Google Colab platform is used with a python interface integrated with Keras and TensorFlow libraries. Finally, all the input images will be converted into 224 X 224 pixels.

Truth data

Classifier results		Class 1	Class 2	Class 3	Class 4	Classification overall	User's accuracy (Precision)
	Class 1	476	0	2	2	480	99.167%
	Class 2	2	462	4	12	480	96.25%
	Class 3	6	54	400	20	480	83.333%
	Class 4	2	24	2	452	480	94.167%
	Truth overall	486	540	408	486	1920	
	Producer's accuracy (Recall)	97.942%	85.556%	98.039%	93.004%		

Overall accuracy (OA): 93.229%

Kappa[1]: 0.91

Figure 4. Confusion Matrix and Performance Metrics of the Proposed Model

Here, the testing dataset contains 480 images that are evenly distributed across four different classes, in order to obtain the desired true positive value:

Class 1: Avian Influenza

Class 2: Coccidiosis

Class 3: Newcastle Disease

Class 4 : Gumboro Disease

Here, the trained model is tested on a different dataset. It is evident from figure 5 that the proposed model has achieved an overall accuracy of 93.2%, while the precision was around 94%. Recall value is .92 and F1 Score is .94

4.1 Comparative Analysis with other Trained Models and Proposed Model

Here, we have compared the proposed model with other existing pre-trained models like VGG-16 and RESNET-50. The comparative outcome analysis is illustrated in Table -2.

Table 2. Comparative Analysis in terms of Accuracy

Model	Training	Testing	Validation
VGG-16	97.5	92.6	89.92
RESNET-50	87.6	78.92	75.66
PROPOSED CNN	98.82	93.22	96.65

Analyzing the outcomes of the proposed research, it is evident that the proposed model has leveraged an enhanced performance in terms of successfully categorizing various poultry diseases. Notably, during evaluation, the proposed model has outperformed other state-of-the-art models when subjected to a test set. The potential advantage of the proposed model lies in its layered neural network architecture. This reduction in size is attributed to the optimization of parameters, rendering the proposed model to be particularly well-suited for applications that demand minimal computational resources. The obtained results showcase that the proposed methodology for identifying poultry diseases is highly efficient in terms of enhanced precision and accuracy.

5. Conclusion

In conclusion, this research has imparted a significant advancement in poultry disease detection with the integration of deep learning. Leveraging a dataset of 2800 images across four distinct disease classes, the proposed Convolutional Neural Network (CNN) model demonstrated effective performance, achieving an accuracy of 98.82% on the training set, 93.22% on the testing set, and 96.65% on the validation set. Outperforming other state-of-the-art models, the proposed model has incorporated a streamlined architecture, making it computationally efficient and practical for deployment in real-time poultry farming scenarios. The precision and accuracy of the proposed methodology underscore its potential impact on early and accurate identification of poultry diseases. This research lays a foundation for future advancements in highlighting the transformative potential of innovative technologies in the agricultural sector.

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