IJERST

International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 21 No. 2 (2025)

ijerst.editor@gmail.com

editor@ijerst.com

ISSN 2319-5991 www.ijerst.com
Vol. 21, No. 2, 2025

Research Paper

LIGHTWEIGHT DEEP LEARNING BASED AUTOMATED POULTRY DISEASE DIAGNOSIS SYSTEM

Anil Kumar Yadav Mekala[1*], M. Aakash[2], V. N. Shiva Ramakrishna[2], K. Hemanth kumar[2], M. Pavan Kumar[2]

[1]Assistant Professor, [2]UG Student, [1,2]Department of Computer Science and Engineering-Data Science, [1,2]Malla Reddy Engineering College and Management Sciences, Kistapur, Medchal, 501401, Telangana, India

**Corresponding author: anilkumar@mrem.ac.in*

ABSTRACT

Poultry farming plays a vital role in ensuring global food security; however, infectious diseases remain a persistent threat to flock health, productivity, and economic stability. Conventional poultry disease diagnosis depends on visual assessment by farm workers and laboratory-based tests such as bacterial cultures and PCR, which are often expensive, time-consuming, and inaccessible to farmers in rural or resource-limited regions. These delays in diagnosis allow diseases such as coccidiosis, Newcastle disease, and avian influenza to spread rapidly, increasing mortality rates and antibiotic usage. Moreover, early-stage symptoms are often subtle and easily missed, reducing the reliability of manual screening. To address these challenges, this research proposes an automated, image-based poultry disease diagnostic system using deep learning and transfer learning techniques. The system integrates pre-trained convolutional neural network models InceptionV3, MobileNetV2, and VGG16 to efficiently extract disease-specific features from poultry images while maintaining manageable computational requirements. A Tkinter-based graphical user interface enables farmers to upload images, perform analysis, and receive rapid diagnostic feedback without specialized technical knowledge. By providing on-farm, real-time disease classification, the proposed system reduces dependence on veterinary laboratories, shortens diagnostic turnaround time, and supports timely disease control decisions. Overall, this work contributes a practical, accessible, and accurate solution for improving poultry health management and minimizing economic losses.

Keywords: Poultry Disease Detection, Deep Learning, Transfer Learning, Convolutional Neural Networks, Image Classification, Precision Agriculture, Veterinary Diagnostics

Received: 02-03-2025 Accepted: 27-04-2025 Published: 06-05-2025

1. INTRODUCTION

Poultry farming plays a crucial role in India's agricultural and economic landscape, contributing significantly to the nation's food security and rural employment. India ranks among the top five poultry producers globally, with an estimated production of over 125 billion eggs and 4.5 million metric tons of poultry meat annually. The poultry sector has experienced rapid growth, with a 6–8% annual increase, largely due to advancements in breeding, nutrition, and disease management. However, poultry diseases such as Newcastle disease, avian influenza, fowl cholera, and infectious bronchitis continue to threaten poultry health, leading to severe economic losses. According to the Indian Ministry of Agriculture, disease outbreaks cause a 15–20% annual loss in poultry production. Traditionally, disease detection relies on manual inspection, post-mortem analysis, and laboratory testing, which are time-consuming, expensive, and require trained veterinarians. Limited access to veterinary care in rural areas exacerbates the issue, leading to delayed diagnosis and disease spread. Recent advancements in artificial intelligence (AI) and deep learning offer a promising solution by automating disease detection through image-based analysis. With 70% of India's poultry production coming from small and medium-scale farms, scalable, cost-effective, and real-time diagnostic solutions are essential for mitigating disease outbreaks and ensuring sustainable poultry farming.

2. LITERATURE SURVEY

Animal agriculture is extremely important to the world's rising population. Animal products provide nutrient-dense meals that help people of all ages stay healthy in communities all over the world. The agriculture business must continue to improve its efficiency and quantity of production as human demand for animal proteins increases [1]. Poultry is widely recognized as a valuable source of protein, and many countries will be forced to increase output, resulting in an increase in the number of farms housing birds at high densities. Furthermore, Poultry farming is crucial for socioeconomic development of developing countries because it provides eggs and meat, which help to ensure food and nutrition security at the household, regional, and national levels. moreover, it provides cash income to the population and adds more than a hundred million dollars to the gross domestic product of a country [2, 3]. As poultry farming Increases, it can promote increased transmission of infectious illnesses among birds which can cause widespread death in poultry and significant economic losses [4]. Every year, 69 billion chickens are reared for meat production around the world [5]. However, not all of them end up on people's tables. Several million chickens do not make it through the rearing process and are likely to be rejected at the butcher due to sickness, scrapes, bruises, and other symptoms of mistreatment. Given the disparity between food accessibility and hunger for certain individuals, especially for farmers, slaughterhouse rejection of hens can be a significant source of financial loss [6–8].

The high frequency of chicken diseases can be linked to a lack of biosecurity, low vaccination coverage, unscientific poultry management methods, and essentially non-existent poultry veterinary interventions throughout the country, particularly in the vast poultry production sector. The most common chicken diseases include fowl cholera, helminth infestation, salmonella infections, avian coccidiosis, and Newcastle disease [9]. Salmonella is a gastrointestinal infection. Infected birds can recover after a period of time, but some continue to discharge bacteria in their droppings for months [10]. When placed on permanent bedding, it is quite impossible to rid a salmonella-infected flock of the virus. Its symptoms include weakness, loss of appetite, stunted growth, and white, loose faces. If young chickens show indicators of significant mortality (up to 100%) and irregular growth [11].

Biochemical testing of chicken faces employing lysine iron and triple sugar iron agar slants can detect the presence of salmonella in addition to the symptoms [12]. On the other hand, Coccidiosis is caused by phylum Apicomplexa, family Eimeriid protozoa. The majority of Eimeria species infect different parts of the intestine in chickens [13]. The infection is quick (4–7days) and is marked by parasite proliferation in host cells as well as significant destruction to the intestinal mucosa [14]. Coccidia in poultry are usually host-specific, with different species parasitizing different regions of the gut [14]. Its symptoms include slowed growth, a high percentage of visibly unwell birds, severe diarrhoea, and a high fatality rate. The amount of food and water consumed is low. Weight loss, culling, decreased egg production, and higher mortality may occur as a result of outbreak [14]. The presence of this disease can be also determined by the location in the host, the appearance of lesions, and the size of oocysts. Oocysts in faces or intestinal scrapings are a simple way to confirm Coccidiosis infections [14].

The other most common poultry disease, new castle disease, is a highly contagious bird disease that affects both domestic and wild birds [15]. It affects birds and poultry's respiratory, neurological, and digestive systems. Because the disease is so deadly, many birds and poultry die without showing any symptoms. A state of prostration and depression in the birds, with ruffled feathers; greenish white diarrhoea; and, in survivors, the head turned to one side, a condition known as torticollis, as well as paralysis of the legs, wings, or other neurological signs, are all common clinical signs of new castle disease [15]. The research of computer vision, imaging processing and pattern recognition has made substantial progress during the past several decades. Nowadays, due to availability of large amount of data and sophisticating algorithms such as deep learning, researchers and industries are employing the technique to solve variety of problems ranging from simple object detection up to complex scene understanding [16].

Especially in health care applications, computer vision and deep learning become successfully for disease detection, classification, and localization. Predicting infectious disease in poultry is becoming possible as new technologies are increasing the availability of data that can be utilized in predictive models [4]. With the development of computer vision systems, computerized disease diagnosis and detection of sick birds have been reported in several studies [17]. performed a skeleton analysis for early detection of sick broilers by image processing. Additionally, Zhuang and Zhang [18] reported on a sick broiler detector based on deep learning techniques. The analysis of chicken droppings by image processing and deep learning for sick bird detection is reported by Wang et al. [19]. However, the study it limited to detecting the abnormality of the faecal image and does not detect the presence of a disease directly. Similarly, a deep Convolutional Neural Network (CNN) model was developed to diagnose poultry diseases by classifying healthy and unhealthy fecal images by Machuve et al. [20]. However, the models were trained using entire acquired images without utilizing object extraction (detection). This approach may result in reduced classification accuracy, as the presence of non-target objects in the images may negatively impact the training process. The objective of this study is to develop an automated computer vision system capable of identifying and classifying chicken diseases through the analysis of chicken facial images. To achieve this goal, we employed advanced object detection algorithms using YOLO v3 and pretrained image classification algorithms using ResNet-50 to detect and classify prevalent poultry diseases. Additionally, a mobile application interface was developed to ensure easy access to the system for poultry farmers and veterinarians.

3. PROPOSED METHODOLOGY

This Tkinter-based desktop application is designed to automate the identification of common poultry diseases from image data. Rather than relying on manual inspection, the system leverages three state-of-the-art convolutional neural network (CNN) architectures (InceptionV3, MobileNetV2, and VGG16) to train and evaluate classification models on a labeled dataset of poultry images.

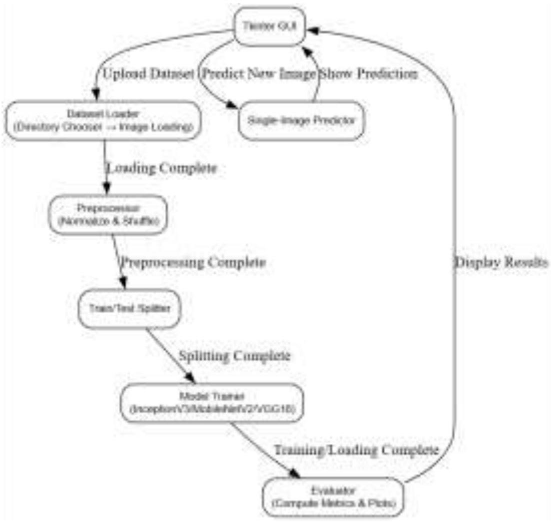

Fig. 1: Block diagram of the proposed poultry disease diagnosis system.

The proposed system is designed to provide an end-to-end, user-friendly framework for poultry disease diagnosis using deep learning, integrating streamlined dataset management, automated preprocessing, model training, evaluation, and inference within a graphical user interface (GUI). Users organize disease images into class-wise subfolders, which the application automatically scans to load and cache resized images (80×80 pixels) with corresponding labels, while instantly visualizing class distributions through a bar chart. With a single click, the system normalizes pixel values, shuffles data, converts labels to one-hot encoding, and splits the dataset into 80% training and 20% testing sets with detailed logs. The framework employs transfer learning using InceptionV3, MobileNetV2, and VGG16 architectures pre-trained on ImageNet, freezing base layers and attaching a custom classification head for disease prediction, with automated weight loading or training as required. Model performance is evaluated using accuracy, precision, recall, and F-score, along with confusion matrices and ROC curves for clear visual analysis. A comparison graph enables side-by-side evaluation of all models, while a single-image inference module predicts disease labels on new images and displays results visually. All functionalities are seamlessly integrated into an intuitive GUI with organized buttons, real-time logs, and a consistent visual design, ensuring efficiency, clarity, and practical usability.

VGG16 Model

VGG16 provides a straightforward yet powerful feature extractor with uniform 3×3 convolutional kernels stacked in depth. After loading include_top=False and freezing its convolutional layers, we attach our standard classification head to convert VGG16's high-dimensional feature maps into disease probabilities. Though VGG16 has more parameters than MobileNetV2, its simple and consistent architecture often yields robust feature representations. By training only the top layers, we capitalize on VGG16's discriminative power while avoiding overfitting on our comparatively small poultry dataset.

In the model building and training phase, we employ transfer learning by importing three pre-trained convolutional neural network architectures—InceptionV3, MobileNetV2, and VGG16 from Keras. Each base model's convolutional layers are frozen to preserve the rich feature representations learned on ImageNet, and a lightweight classification head (average pooling → flatten → dense → dropout → softmax) is appended. Models are compiled with the Adam optimizer and categorical cross-entropy loss before training for 40 epochs (batch size 64) on the poultry dataset's 80×80 normalized images. Checkpoint callbacks save the best weights on disk, allowing future runs to skip full retraining and load pre-existing weights directly. After training or weight loading, each model performs inference on the held-out test set and passes predictions to the evaluation module for metric computation and visualization.

Step1: Load Pre-trained Base

- Use Keras' InceptionV3/MobileNetV2/VGG16 with include_top=False and weights='imagenet'.
- Input shape is set to match our 80×80×3 images.
- Freeze all convolutional layers so that their weights remain unchanged during training.

Step 2: Attach Custom Classification Head

- Take the output tensor of the frozen base.
- Apply AveragePooling2D(pool_size=(1,1)) to reduce spatial dimensions.
- Flatten the pooled features via Flatten(name="flatten").
- Add a dense layer (Dense(128, activation="relu")) to introduce a learnable fully connected block.
- Apply Dropout(0.3) to reduce overfitting.
- Final layer: Dense(num_classes, activation="softmax") produces class probabilities over poultry disease labels.

Step 3: Compile the Model

- Optimizer: Adam (optimizer="adam")

International Journal of Engineering Research and Science & Technology

- Loss function: Categorical cross-entropy (loss="categorical_crossentropy")
- Metrics: Track accuracy during training.

Step 4: Training or Weight Loading

- If the file model/inceptionv3_weights.hdf5 or model/mobilenetv2_weights.hdf5 or model/vgg16_weights.hdf5 does **not** exist:
    - Fit the model for 40 epochs with batch_size=64, validating on (X_test, y_test).
    - Use ModelCheckpoint(filepath="model/inceptionv3_weights.hdf5 or model/mobilenetv2_weights.hdf5 or model/vgg16_weights.hdf5", save_best_only=True) to save only the epoch with the lowest validation loss.
    - Serialize training history to model/inceptionv3_history.pckl or model/mobilenetv2_history.pckl or model/vgg16_history.pckl for later analysis.
- Otherwise, directly load weights via inceptionv3_model.load_weights("model/inceptionv3_weights.hdf5" or model/mobilenetv2_weights.hdf5 or model/vgg16_weights.hdf5") and skip retraining.

Step 5: Inference & Evaluation

- Call inceptionv3_model.predict(X_test) to obtain per-class probabilities.
- Convert probabilities to integer labels via np.argmax(...).
- Compare with ground-truth one-hot labels (converted to integers via np.argmax(y_test, axis=1)).
- Pass these predicted and true labels to a metrics function that computes accuracy, precision, recall, F1-score, confusion matrix, and ROC curve.

4. Results description

Fig. 2 illustrates how many images belong to each disease class in the uploaded poultry dataset. The x-axis lists the distinct class labels (e.g., "Healthy," "Coccidiosis," "Newcastle Disease," etc.), arranged horizontally with a 90° rotation for readability. The y-axis indicates the count of images per class. Visualizing class distribution helps the user verify that no class is drastically underrepresented before proceeding to training. Fig. 9.3 shows the updated GUI state. This immediate feedback assures the user that image ingestion succeeded and provides a summary of dataset characteristics.

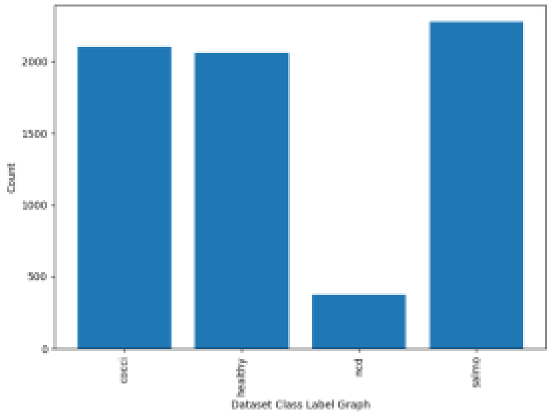

Fig. 2: Class distribution versus number of images.

In Fig. 3, the evaluation results for the VGG16 based classifier are shown. The confusion matrix heatmap typically exhibits the highest concentration of true-positive counts along the diagonal, indicating that VGG16 attains the fewest misclassifications among the three models. Misclassifications (off-diagonal cells) are minimal and often occur between visually similar disease classes such as "Marek's Disease" versus "Infectious Bronchitis." On the ROC plot, the curve hugs the top-left boundary more tightly than both InceptionV3 and MobileNetV2, yielding the highest AUC (e.g., ~0.99). This corroborates VGG16's marginally superior numeric performance (Accuracy ~98.83%, F-Score ~98.35%). Together, these visualizations confirm that VGG16 achieves the best class discrimination and overall predictive reliability.

IJERST International Journal of Engineering Research and Science & Technology

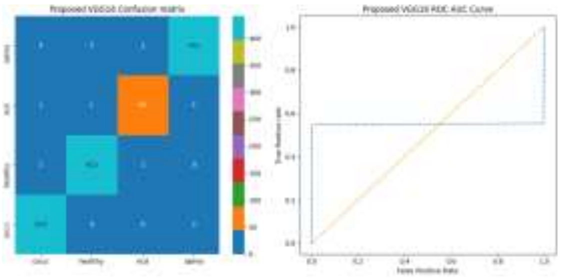

Fig. 3: Obtained confusion matrix, AUC, and ROC curve using VGG16 model.

Table 1 compares the performance of InceptionV3, MobileNetV2, and the proposed VGG16 model using Accuracy, Precision, Recall, and F-Score on the poultry disease test dataset. The proposed VGG16 achieves the best overall performance with the highest accuracy (98.83%), precision (98.48%), recall (98.22%), and F-score (98.35%), demonstrating superior and well-balanced classification capability. InceptionV3 closely follows with comparable results across all metrics, indicating strong and consistent performance. In contrast, MobileNetV2 shows relatively lower accuracy (97.43%) and noticeably reduced recall (94.79%), suggesting a higher rate of missed disease cases. Consequently, MobileNetV2's lower recall significantly impacts its F-score (95.67%). Overall, the results confirm that VGG16 is the most reliable architecture for poultry disease classification among the evaluated models.

Table 1: Performance comparison of quality metrics obtained using transfer learning models (InceptionV3, MobileNetV2, and VGG16).

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F-Score (%)**
InceptionV3	98.75	98.43	98.14	98.28
MobileNetV2	97.43	96.68	94.79	95.67
Proposed VGG16	98.83	98.48	98.22	98.35

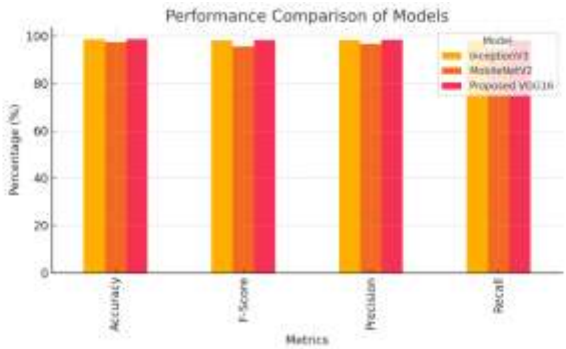

Fig. 4: Performance comparison graph of existing and proposed models.

Fig. 4 clearly shows that all three transfer learning–based models achieve excellent classification performance (Accuracy > 97%). However, the proposed VGG16 model outperforms both InceptionV3 and MobileNetV2 by a small but meaningful margin across Accuracy, Precision, Recall, and F-Score, making it the optimal choice for automated, reliable poultry disease diagnosis on this ataset.

(a)

(b)

Fig. 5: Sample predictions on test images. (a) healthy. (b) cocci.

Fig. 5 illustrates sample predictions produced by the proposed VGG16-based poultry disease classification system. In subfigure (a), the test image depicts a healthy poultry specimen with no visible signs of disease, such as lesions, discoloration, or abnormal posture; after preprocessing and inference, the system correctly classifies the image as Healthy, displaying the prediction in blue text on the output window. In subfigure (b), the test image shows subtle visual symptoms associated with coccidiosis, including slight darkening near the vent area and a mildly lethargic stance. Despite the subtle nature of these indicators, the model accurately identifies the infection and overlays the predicted label *Cocci* in red text, demonstrating its capability to detect fine-grained disease patterns that may be difficult to recognize through manual observation.

5. CONCLUSION

This study presented a transfer learning–based poultry disease diagnosis system that integrates InceptionV3, MobileNetV2, and a proposed VGG16 model within a user-friendly Tkinter GUI for automated image-based disease classification. Experimental evaluation demonstrates that the VGG16 pipeline delivers superior and well-balanced performance, achieving 98.83% accuracy, 98.48% precision, 98.22% recall, and a 98.35% F-score, outperforming InceptionV3 with marginal yet meaningful gains and significantly surpassing MobileNetV2 across all metrics. These improvements reflect a notable reduction in false positives and false negatives, which is critical for reliable farm-level disease detection. The enhanced performance is attributed to VGG16's uniform 3×3 convolutional architecture, which effectively captures fine-grained visual features associated with poultry diseases, along with an efficient transfer learning strategy that ensures fast convergence without overfitting. In addition to high classification accuracy, the system offers practical advantages such as rapid image preprocessing, flexible model training or weight loading, detailed performance visualization through confusion matrices and ROC curves, and real-time single-image inference within 200 ms. Overall, the proposed system serves as a dependable and accessible decision-support tool for poultry farmers, enabling early disease detection, reducing dependence on laboratory testing, and contributing to improved flock health and productivity.

REFERENCE

[1] S. Neethirajan, Automated tracking systems for the assessment of farmed poultry, Animals 12 (3) (2022) 232, https://doi.org/10.3390/ani12030232.

[2] Conan FLG, S. Sorn, S. Vong, Biosecurity measures for backyard poultry in developing countries: a systematic review, BMC Vet. Res. 8 (2012) 240.

[3] B.I. Shapiro, G. Gebru, S. Desta, A. Negassa, K. Nigussie, G. Aboset, H. Mechal, Ethiopia Livestock Master Plan, International Livestock Research Institute (ILRI), Nairobi, Kenya, 2015.

[4] J. Astill, R.A. Dara, E. Fraser, S. Sharif, Detecting and predicting emerging disease in poultry with the implementation of new technologies and big data: a focus on Avian influenza virus, Frontiers in veterinary science 5 (2018).

[5] H. Ritchie, P. Rosado and M. Roser, Meat and Dairy Production. Published online at OurWorldInData.org. Retrieved from: 'https://ourworldindata.org/meatproduction' [Online Resource]. 2017.

[6] B.B. Xavier Averos, ´ E. Cameno, I. Estevez, The value of a retrospective analysis of slaughter records for the welfare of broiler chickens, Poult. Sci. (2020).

[7] T.E.K.E. Bulent, Survey on dead on arrival of broiler chickens under commercial transport conditions, Large Anim. Rev. (2019) 237–241.

[8] C. Beretta, F. Stoessel, U. Baier, S. Hellweg, Quantifying food losses and the potential for reduction in Switzerland, Waste Manag. 33 (3) (2013) 764–773, https://doi.org/10.1016/j.wasman.2012.11.007. ISSN 0956-053X.

[9] G.A. Yohannes Asfaw, Girmay Medhin,Gezahegn Alemayehu,Barbara WielandPublication. Nfectious and Parasitic Diseases of Poultry in Ethiopia:a systematic Review and Meta-Analysisauthor, Poultry SciencePublisher, 2019.

[10] Reddy, S. K. R. Tailoring Loyalty Rewards Systems across Industries: Cloud vs On-Prem Solutions. International Journal of All Research Education and Scientific Methods (IJARESM),April 2025, ISSN: 2455-6211.

[11] Nandigama, N. C. (2022). Machine Learning–Enhanced Threat Intelligence for Understanding the Underground Cybercrime Market. International Journal of Intelligent Systems and Applications in Engineering. Internet Archive. https://doi.org/10.17762/ijisae.v10i2s.7972.

[12] Kagamb`ega, A. Thibodeau, V. Trinetta, D.K. Soro, F.N. Sama, E. ´ Bako, C. S. Bouda, A. Wereme N'Diaye, P. Fravalo, N. Barro, Salmonella spp. and campylobacter spp. in poultry feces and carcasses in Ouagadougou, Burkina Faso, Food Sci. Nutr. 6 (6) (2018) 1601–1606.

[13] A.J. Fatoba, M.A. Adeleke, Diagnosis and control of chicken coccidiosis: a recent update, J. parasit. dis.: off. organ Indian Soc. Parasitol. 42 (4) (2018) 483–493.

[14] Nandigama, N. C. (2016). Teradata-Driven Big Data Analytics For Suspicious Activity Detection With Real-Time Tableau Dashboards. International Journal For Innovative Engineering and Management Research, 5(1), 73–78.

[15] M. Getabalew, T. Alemneh, D. Akeberegn, D. Getahun, D. Zewdie, Epidemiology, diagnosis & prevention of Newcastle disease in poultry, Am. J. Biomed. Sci. Res. 3 (1) (2019) 50–59, https://doi.org/10.34297/AJBSR.2019.03.000632. AJBSR. MS. ID.000632.

[16] Esteva, K. Chou, S. Yeung, et al., Deep learning-enabled medical computer vision, NPJ Digit. Med. 4 (2021) 5, https://doi.org/10.1038/s41746-020-00376-2.

[17] X. Zhuang, M. Bi, J. Guo, S. Wu, T. Zhang, Development of an early warning algorithm to detect sick broilers, Comput. Electron. Agric. 144 (2018) 102–113.

[18] X. Zhuang, T. Zhang, Detection of sick broilers by digital image processing and deep learning, Biosyst. Eng. 179 (2019) 106–116.

[19] J. Wang, M. Shen, L. Liu, Y. Xu, C. Okinda, Recognition and classification of Broiler droppings based on deep convolutional neural network, J. Sens. 2019 (2019), 3823515, https://doi.org/10.1155/2019/3823515, 10.

[20] D. Machuve, E. Nwankwo, N. Mduma, J. Mbelwa, Corrigendum: poultry diseases diagnostics models using deep learning, Front. Artif. Intell. 5 (2022), 1016695.