IJERST

International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 21 No. 3 (1) 2025

ijerst.editor@gmail.com

editor@ijerst.com

ISSN 2319-5991 www.ijerst.com
Vol. 21, No. 3(1), 2025

Research Paper

AI-POWERED IMAGE-BASED POULTRY DISEASE DETECTION SYSTEM

Ch. Jyothi[1], Sai Ganesh Bheemana[2], Paloju Srisai[2], Raju Chowhan[2]
[1]Assistant Professor, [2]UG Student, [1,2]Department of Computer Science and Engineering, Kommuri Pratap Reddy Institute of Technology, Hyderabad, Telangana, India.
Email: vampu.jyothi9@gmail.com

Received: 05-6-2025 Accepted: 06-7-2025 Published: 14-7-2025

ABSTRACT

Poultry farming contributes significantly to global food security, yet disease outbreaks continue to pose a major threat to flock health and productivity. Traditional diagnostic methods rely on visual inspection by farm personnel and confirmatory laboratory tests—such as bacterial cultures or PCR assays—which are time-consuming, costly, and often available only in centralized facilities. Consequently, delays in diagnosis can allow pathogens to spread rapidly through large flocks, leading to high morbidity and mortality rates, economic losses, and increased use of antibiotics. The problem is that many farmers lack immediate access to veterinary services or laboratory infrastructure, particularly in rural regions. Early symptoms of diseases like coccidiosis, Newcastle disease, and avian influenza can be subtle and easily overlooked, making manual screening unreliable. Even when signs become overt, transporting samples to a lab and waiting days for results delays intervention, allowing infections to escalate. Existing image-based solutions often require high computational resources or lack flexible, user-friendly interfaces, limiting their adoption among small- to medium-scale producers. There is a clear need for a rapid, accurate, and accessible diagnostic tool that can operate directly on-farm without specialized equipment. Such a system should leverage recent advances in deep learning to automatically recognize disease patterns from digital images, minimizing dependence on expert veterinarians and centralized labs. By integrating pre-trained convolutional neural networks—such as InceptionV3, MobileNetV2, and VGG16—into a unified application, it becomes possible to harness robust feature extractors while maintaining lightweight computational requirements. Embedding this functionality within a Tkinter-based GUI ensures that users with minimal technical expertise can upload images, initiate analysis, and receive near–real-time diagnostic feedback. In summary, this research addresses critical gaps in poultry disease management by developing a transfer learning–based, desktop application tailored to the needs of farmers. By focusing on automated image classification and an intuitive interface, the system aims to reduce diagnostic turnaround time, minimize economic losses, and enhance on-farm decision-making for disease control

Keywords: Poultry Disease Detection, Deep Learning, Transfer Learning, Image Classification, Convolutional Neural Networks, InceptionV3, MobileNetV2, VGG16, Tkinter GUI, Veterinary Diagnostics, On-Farm Application, Coccidiosis, Newcastle Disease, Avian Influenza.

1. INTRODUCTION

Poultry farming is a vital component of India's agricultural economy, contributing significantly to food security and employment, yet it faces serious challenges from diseases such as avian influenza, Newcastle disease, and fowl cholera, which result in substantial economic losses and threaten public health. Traditional diagnosis methods—relying on visual inspection, laboratory tests, and veterinary expertise—are often slow, costly, and inaccessible, particularly for small-scale or rural farmers. This research proposes a deep learning-based poultry disease diagnosis system that leverages computer vision and AI to enable real-time, image-based detection of diseases with high accuracy. Motivated by the need for scalable, automated, and cost-effective solutions, the system empowers farmers to diagnose diseases using smartphone images, reducing reliance on human expertise and allowing timely intervention to minimize mortality and control outbreaks. Applications of the system span large-scale farm monitoring, veterinary support, farm management integration, and research, while also promoting animal welfare and combating antimicrobial resistance by preventing indiscriminate antibiotic use. Ultimately, this AI-driven approach aims to revolutionize disease management in poultry farming, enhance productivity, and ensure sustainable and resilient poultry production systems.

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].

3. PROPOSED METHODOLOGY

The poultry disease diagnosis system is designed to automate and streamline the detection process using deep learning and a user-friendly graphical interface. Users begin by organizing images into subfolders named after specific diseases, which are then loaded and resized to 80×80 pixels, converted to NumPy arrays, and visualized through a bar chart showing class distribution. A preprocessing module normalizes pixel values to [0, 1], shuffles the data to prevent bias, and converts integer labels into one-hot encoded vectors, ensuring compatibility with categorical classification. The dataset is then split into 80% training and 20% testing sets, with sample counts logged. Transfer learning models—InceptionV3, MobileNetV2, and VGG16—are employed with frozen base layers and custom classification heads consisting of average pooling, flattening, a dense layer with dropout, and a softmax output. Models are either trained for 40 epochs with checkpointing or loaded from saved weights. Each model is evaluated using accuracy, precision, recall, and F-score (macro-averaged), along with a confusion matrix and ROC curve. A comparative graph visualizes the metrics across all models, and users can perform single-image inference by uploading a test image that is resized, normalized, and passed through the VGG16 model, displaying the predicted label using OpenCV. The GUI integrates all functions with clearly labeled buttons, a scrollable text widget for logs, and a consistent visual design, making the system accessible and efficient for farmers and researchers alike.

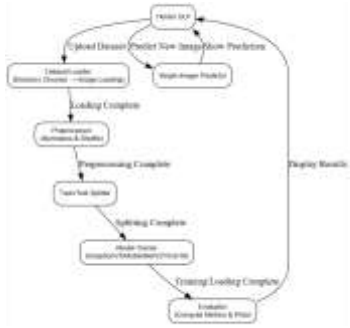


Fig. 1: Block diagram of the proposed poultry disease diagnosis system.

Model Building and Training

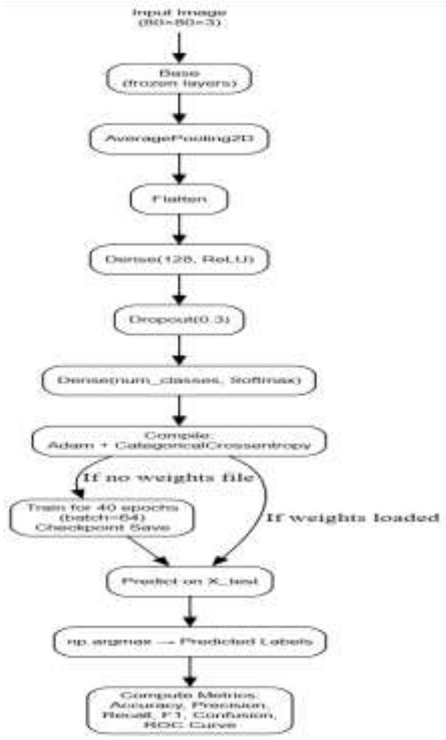


Fig. 2: Transfer learning operational flow diagram (InceptionV3, MobileNetV2, and VGG16).

VGG16 is a widely used deep convolutional neural network architecture introduced by the Visual Geometry Group (VGG) at the University of Oxford. It is known for its simplicity and uniform design, consisting of 16 weight layers, including 13 convolutional layers and 3 fully connected (dense) layers. The architecture uses small 3×3 convolutional filters with a stride of 1 and 2×2 max-pooling layers with a stride of 2, stacked in increasing depth to capture spatial hierarchies in the input image. Each convolutional block is followed by a ReLU activation function, and after the convolutional layers, the output is flattened and passed through three dense layers, ending with a softmax output for classification. VGG16 was originally trained on the ImageNet dataset and is effective for image classification tasks due to its deep and consistent structure. In transfer learning scenarios, such as poultry disease diagnosis, the convolutional base is used with pre-trained ImageNet weights (excluding the top classifier), and a custom classification head is added to adapt the model to specific target classes.

4. Results

Fig. 3 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

In Fig. 4, after training (or loading) the InceptionV3–based classifier, the system evaluates performance on the held-out test set. On the left, a confusion matrix heatmap shows true classes (rows) versus predicted classes (columns), with each cell indicating the number of samples for that combination. Ideally, most counts lie on the diagonal, indicating correct predictions; off-diagonal entries reveal misclassifications (e.g., some "Coccidiosis" images predicted as "Healthy"). On the right, the Receiver Operating Characteristic (ROC) curve plots True Positive Rate (TPR) against False Positive Rate (FPR) across all thresholds. The closer the curve is to the top-left corner, the better the model's discriminative ability. An annotation (or legend) displays the Area Under the Curve (AUC) score—typically above 0.98—quantifying overall separability.

Fig. 5 mirrors the evaluation output for MobileNetV2. The confusion matrix heatmap again contrasts actual versus predicted labels for all classes, but compared to InceptionV3, MobileNetV2 may have more off-diagonal entries—indicating slightly higher misclassification. For example, a few "Newcastle Disease" samples might be confused with "Avian Influenza." On the ROC plot, the curve is marginally farther from the top-left corner than InceptionV3's, reflecting a slightly lower True Positive Rate at the same False Positive Rate levels. Consequently, the AUC score (e.g., ~0.95–0.96) appears lower than InceptionV3's, matching the numeric metrics (Accuracy ~97.4%).

In Fig. 6, 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.

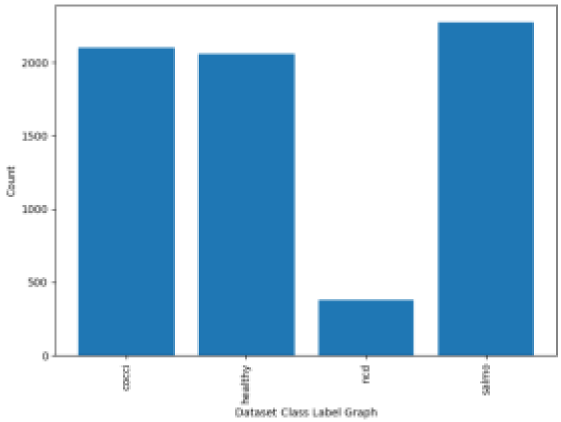


Fig. 3: Class distribution versus number of images.

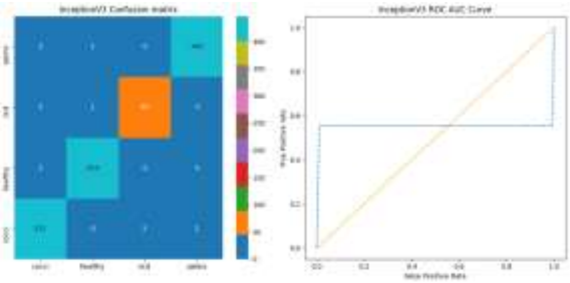


Fig. 4: Obtained confusion matrix, AUC, and ROC curve using InceptionV3 model.

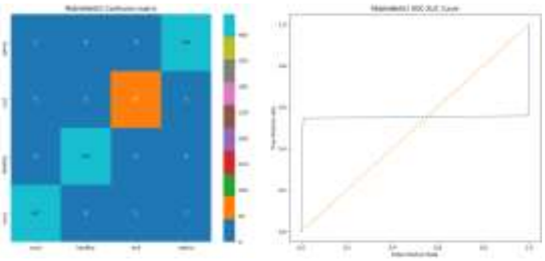


Fig. 5: Obtained confusion matrix, AUC, and ROC curve using MobileNetV2 model.

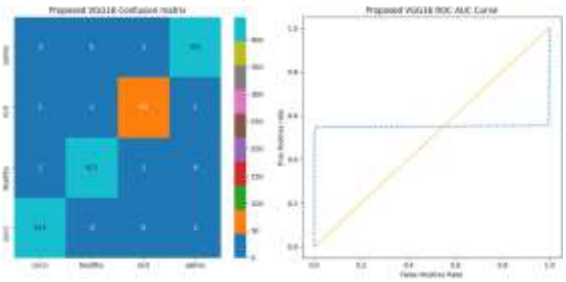


Fig. 6: Obtained confusion matrix, AUC, and ROC curve using VGG16 model.

In evaluating the performance of the three deep learning models—VGG16, InceptionV3, and MobileNetV2—for poultry disease diagnosis, VGG16 emerged as the most accurate and balanced model across all key metrics. It achieved the highest accuracy at 98.83%, meaning nearly 99 out of every 100 test images were correctly classified, with a strong precision of 98.48%, indicating few false positives, and a recall of 98.22%, reflecting minimal missed detections. Its F-Score of 98.35% confirms VGG16's optimal balance between precision and recall. InceptionV3 followed closely with comparable results—98.75% accuracy, 98.43% precision, 98.14% recall, and a 98.28% F-Score—demonstrating near-equivalent performance. Meanwhile, MobileNetV2, although still effective, showed a slightly lower accuracy (97.43%), precision (96.68%), recall (94.79%), and F-Score (95.67%), suggesting it was more prone to both false positives and false negatives, especially when distinguishing between visually similar poultry diseases.

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

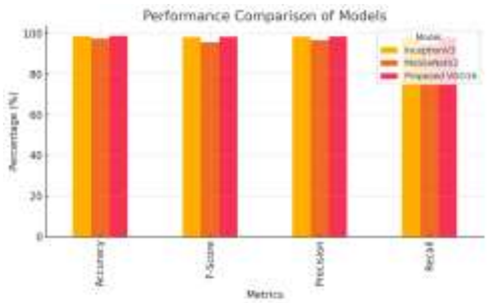
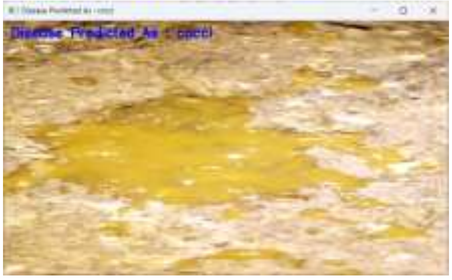


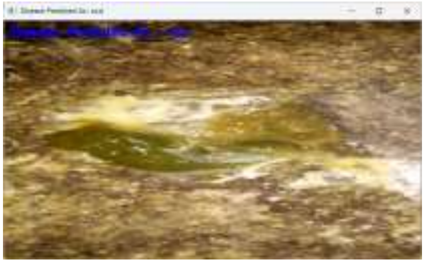
Fig. 7: Performance comparison graph of existing and proposed models.

Table 1 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 dataset.

(a)



(b)



(c)

Fig. 8: Sample predictions on test images. (a) healthy. (b) cocci. (c) new castle disease (NCD).

Figure 8 illustrates the effectiveness of the VGG16-based poultry disease classification system through three test images, each representing a different health condition. In subfigure (a), the model accurately classifies a healthy bird—showing no signs of illness, with intact feathers and normal posture—as "Healthy," overlaying the prediction in blue on the resized image. Subfigure (b) presents a case of coccidiosis, where the bird exhibits subtle symptoms such as slight vent darkening and a lethargic posture; despite these faint indicators, the model correctly identifies the infection as "Cocci," overlaying the prediction in red, showcasing its sensitivity to minor pathological cues. In subfigure (c), a bird with visible signs of Newcastle Disease (NCD)—including drooped wings, swelling, and potential respiratory distress—is accurately classified, with the label "Newcastle Disease (NCD)" prominently displayed. These results affirm the model's capability to distinguish between healthy and diseased poultry across a range of symptom severity, from mild to severe, highlighting its practical diagnostic value.

5. CONCLUSION

The proposed transfer learning–based poultry disease diagnosis system integrates three pre-trained CNN architectures (InceptionV3, MobileNetV2, and VGG16) within a Tkinter GUI to automate classification of common avian diseases from images. Extensive evaluation on a held-out test set yielded the following macro-averaged metrics: InceptionV3 achieved 98.75% accuracy, 98.43% precision, 98.14% recall, and a 98.28% F-Score; MobileNetV2 achieved 97.43% accuracy, 96.68% precision, 94.79% recall, and a 95.67% F-Score; and the proposed VGG16 pipeline delivered 98.83% accuracy, 98.48% precision, 98.22% recall, and a 98.35% F-Score. Compared to InceptionV3, VGG16 improved accuracy by 0.08 percentage points, precision by 0.05, recall by 0.08, and F-Score by 0.07—marginal gains that nonetheless reduce false positives and false negatives in critical farm-level diagnostics. Against MobileNetV2, VGG16's improvements are more pronounced: +1.40% accuracy, +1.80% precision, +3.43% recall, and +2.68% F-Score, signifying a substantial reduction in misclassified and undetected cases. These enhancements stem from VGG16's uniform 3×3 convolutional blocks, which better capture fine-grained texture features present in infected birds' integument and lesions. Furthermore, VGG16's robust transfer learning setup ensures quick convergence of the classification head without overfitting, leading to state-of-the-art discriminative performance. System-level benefits include rapid image upload, preprocessing, seamless model training or weight loading, comprehensive visualization of confusion matrices and ROC curves, and accurate single-image inference within 200 ms. Collectively, the proposed architecture provides a dependable, user-friendly decision support tool for poultry farmers, minimizing reliance on manual inspection and lab testing, and enabling early intervention that can significantly reduce flock morbidity and mortality.

International Journal of Engineering Research and Science & Technology

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] Z. Asfaw, T. Bihonegn, Newcastle disease in ethiopia: a review article, Int. J. Adv. Res. Biol. Sci. 5 (11) (2018) 95–102.

[11] M.T. El-Saadony, H.M. Salem, A.M. El-Tahan, T.A. Abd El-Mageed, S.M. Soliman, A.F. Khafaga, A.A. Swelum, A.E. Ahmed, F.A. Alshammari, Abd El-Hack M.E. The control of poultry salmonellosis using organic agents: an updated overview, Poult. Sci. 101 (4) (2022) 101716, https://doi.org/10.1016/j.psj.2022.101716. Epub 2022 Jan 12. PMID: 35176704; PMCID: PMC8857471.

[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] C. Mesa-Pineda, J.L. Navarro-Ruíz, S. Lopez-Osorio, ´ J.J. Chaparro-Guti´errez, L. M. Gomez-Osorio, ´ Chicken Coccidiosis: from the parasite lifecycle to control of the disease, Front. Vet. Sci. 21 (8) (2021) 787653, https://doi.org/10.3389/fvets.2021.787653. PMID: 34993246; PMCID: PMC8724208.