Early Disease Detection in Poultry: Potential of Clinical Symptom-Monitoring Technologies

Mr.S.Dilip kumar[1], Dr.K. Jayanthi[2]
[1]*Research Scholar, Department of Computer Science, Government Arts and Science College, Kangeyam*
[2]*Assistant Professor and Head, Department of Computer Science, Government Arts and Science College, Kangeyam*

Abstract: Rising global population and demand for nutritious food drive animal protein consumption, with the poultry industry playing a critical role. Early detection and intervention for infectious poultry diseases are essential for successful production and improved animal welfare. Traditional methods often fall short, leading to decreased productivity and mortality. However, a promising avenue lies in clinical symptom-monitoring technologies. This review examines recent research on these technologies, focusing on their ability to identify sick birds through observable clinical signs like elevated body temperature, abnormal vocalizations, and behavioral changes. The review finds that such technologies offer the potential for continuous, non-invasive, and automated monitoring of poultry health, potentially revolutionizing early warning decision-making on poultry farms. However, further development and optimization are needed to fully leverage their potential for on-farm early disease detection.

Index Terms--**Poultry disease detection, clinical symptom-monitoring, animal welfare, early warning system, automated monitoring.**

1. INTRODUCTION

Early detection of poultry diseases is paramount for mitigating economic losses and safeguarding public health. Bacterial infections like Clostridium, causing necrotic enteritis, and Salmonella, responsible for human foodborne illnesses, pose significant threats to the poultry industry. Traditional laboratory diagnostic methods, while effective, can be expensive and time-consuming, hindering timely intervention. The emergence of deep learning offers a promising avenue to automate and expedite disease detection using image analysis, potentially revolutionizing poultry health management.

To emphasize the significance of the YOLOv8-based model in improving broiler monitoring and suggesting implications for the broader field of agricultural technology and animal care. Provide an overview of the challenges in intensive poultry production, emphasizing the importance of continuous monitoring for early detection and prevention of health issues in broilers [1]. The study enhances YOLOv5 with the mobile-EMO network for precise caged broiler health detection. Results show improved accuracy and efficiency, benefiting poultry farming economics and disease prevention in intensive broiler production [2]. For Behavior recognition algorithm using U-Net and MoviNet-A4 to estimate broiler drinking times, advancing farm management with efficient monitoring and data collection [3]. They demonstrate that robotic presence in poultry houses alters broiler spatial behavior, promoting locomotor activity and exploratory behaviors, potentially enhancing welfare and environmental conditions in intensive farming [4]. The model YOLOv5-C3CBAM-BiFPN, enhancing laying hen detection with CBAM and BiFPN integration. Achieving high metrics and real-time capability, it advances feeding management and welfare in poultry farming [5]. It evaluates algorithms, metrics, challenges like target occlusion, and advocates for open datasets. The review highlights potential advancements in crop and livestock management through optimized computer vision techniques and emphasizes the need for model interpretability and sensor integration [6]. Generative Adversarial Networks (GANs) in image processing, covering diverse applications such as image synthesis, generation, semantic editing, image-to-image translation, super-resolution, in painting, and cartoon generation. It analyzes methodologies that have enhanced these applications, explores challenges like training instability, and proposes solutions [7]. It emphasizes advancements in genetic selection leveraging genomics for efficiency, welfare, and market demands. Precision poultry farming is highlighted as pivotal for integrating imaging technologies to assess production and animal wellbeing. Feed formulation adaptation, driven by nutritional needs, ingredient availability, and cost dynamics, is discussed alongside technological innovations in bird processing aimed at enhancing meat quality and reducing labor intensity [8]. New insights from the symposium suggest potential control measures for GD, such as limiting ionophore administration during the broiler life cycle. For NE, advancements include improving vaccination strategies using microscopic polymer beads in gel formulations, which outperformed traditional water spray methods [9]. The various pathogens, including viruses, bacteria, and fungi, can trigger respiratory diseases in poultry. Environmental factors are also noted to exacerbate these pathogens, leading to observable clinical signs and lesions [10].

This research aims to develop a CNN-based system to predict and diagnose Clostridium and Salmonella in poultry accurately. Traditional methods are costly, time-consuming, and often miss timely disease warnings. The system will analyze indicators like vocalization, body temperature, feces, and behaviors to assess poultry health.

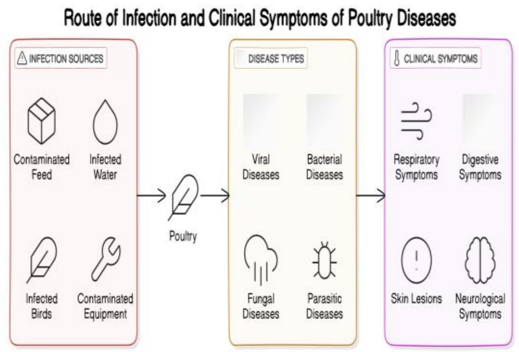

Figure 1. The image shows that clinical symptoms of poultry diseases can be categorized into respiratory symptoms, digestive symptoms, skin lesions, and neurological symptoms.

2. EARLY DISEASES DETECTION THROUGH PHYSIOLOGICAL CHARACTERISTICS

The physiological characteristics of birds hold a wealth of information, often reflecting the comfort of their growing environment, as well as their emotional state and health status. In humans, physiological indicators such as blood biochemical indices, blood pressure, and body temperature are fundamental for disease diagnosis. Similarly, in poultry, physiological characteristics including vocalization, feces, and body temperature are extensively used in disease detection and early warning, as these factors have been shown to be associated with disease. Therefore, this section focuses on the physiological characteristics that are easy to measure and accurately reflect the health status of poultry.

2.1. ABNORMAL VOCALIZATION

Poultry vocalization is a key indicator of health, predicting weight and analyzing pecking activity, which can reflect respiratory health. Variations in vocalizations alert breeders to poor environments or disease. Rales, abnormal respiratory sounds, are common in poultry respiratory diseases. Studies using Mel Frequency Cepstral Coefficients (MFCCs) and classifiers like decision trees, extreme learning machines (ELM), and support vector machines (SVM) have achieved high accuracy in detecting these diseases.

Banakar et al. showed distinct acoustic characteristics in poultry infected with diseases like Newcastle disease (ND), infectious bronchitis disease (IBD), and avian influenza (AI). Sound data classification using SVM and Dempster–Shafer evidence theory achieved 91.15% accuracy. Despite high accuracy in controlled environments, detecting sneezing in noisy farm conditions reached 88.4% accuracy.

Deep learning models like Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) outperform traditional methods by automatically extracting features. Cuan et al. demonstrated CNN's high accuracy in detecting avian influenza and Newcastle disease early, outperforming RNNs significantly. Challenges include environmental noise and the sparsity of abnormal sounds, making it crucial to design algorithms that improve recognition accuracy in noisy environments. Enhancing spatial localization of abnormal sounds could further modernize poultry management and reduce farmer burden.

2.2. ABNORMAL BODY TEMPERATURE

Chickens regulate their body temperature, but stress or disease can cause fluctuations, making temperature a vital indicator for early disease detection. Footpad dermatitis (FPD) causes necrotic lesions on broilers' footpads, impacting welfare and economics. Hoffmann et al. found a negative correlation between the dielectric constant (DC) value and FPD severity, measured using a moisture meter. Thermal imaging revealed lower footpad temperatures in turkeys with FPD, correlating 86.7% with visual scores in chickens, indicating thermal imaging's reliability for early detection.

For avian influenza (AI), thermal imaging and wearable sensors have shown potential for early detection. A decrease in body temperature detected by a thermistor can precede clinical signs of AI.

High-resolution thermal imaging can identify dead chickens, reducing disease risk. Liu et al. used thermal imaging to distinguish healthy and sick chickens based on temperature differences between their heads and legs. Shen et al. achieved 91.3% head recognition accuracy using thermal infrared images.

Future research should improve thermal imaging under variable conditions and enhance the segmentation accuracy of chicken head and leg areas. Exploring the relationship between body temperature, growth, and behavior is also crucial. Wearable sensors need to become more portable, stable, and have longer transmission distances.

2.3. ABNORMAL FECES

Digestive system diseases are among the most common ailments in chicken farming, severely affecting production and animal welfare. When chickens' gastrointestinal tracts are infected by bacteria or viruses, the severity of the infection leads to varying degrees of pathological changes. Clinically, these changes are often indicated by abnormal feces. Figure2 presents examples of normal versus abnormal feces associated with typical digestive diseases in chickens.

Figure2: The feces of chickens suffering from typical digestive diseases can exhibit abnormal changes in color, shape, water content, and overall composition. This contrast between normal and abnormal feces is indicative of disease presence and severity.

Name of Disease	Vulnerable Time	Characteristics
Newcastle disease	All ages	Yellow-brown and watery
Avian influenza	All ages	Yellow-brown and watery
Infections bursa disease	3-6 weeks	Lime watery
Infections bronchitis	3-7 weeks	White and watery
Avian cholera	Adult	Grass-green and watery
Pullorum disease	0-2 weeks	White mushy
Coccidiosis	4-6 weeks	Brown-red thin or blood
Tapeworm disease	All ages	Tapeworm eggs

3. EARLY DISEASE DETECTION THROUGH BEHAVIOURAL CHARACTERISTICS

Behavior, as reflected by activity and posture, is one of the most important indicators of animal welfare and health. It is considered simpler, more commonly used, and easier to understand than stress and production levels. Therefore, real-time, automatic, and non-destructive monitoring of poultry behavior is crucial for improving animal welfare and early detection of sick chickens.

3.1. ABNORMAL ACTIVITY

Lameness is common in poultry, affecting around 30% of chickens, and deviations in activity levels often indicate disease. Kristensen et al. used cameras to monitor broiler chickens' activity, successfully alerting producers to abnormal behaviors. Aydin developed a non-invasive method using a 3D vision camera to detect lying and standing events, achieving 93% accuracy compared to manual scoring. This method correlated lying duration with gait scores and identified other metrics like speed and step frequency related to walking ability decline. Optical flow analysis detected early signs of Campylobacter infection, showing higher mean and lower kurtosis in healthy flocks. This method detected subclinical infections earlier than traditional methods. Monitoring flock activity also predicts conditions like increased mortality and keel bone fractures in laying hens, indicating potential health issues.

Automatic activity monitoring shows promise in early disease detection, though current research focuses on flock-level monitoring. Future advancements targeting individual chickens within a group showing abnormal activity will enhance animal welfare significantly.

3.2. ABNORMAL POSTURE

Zhuang et al. used segmentation algorithms to distinguish healthy and AI-infected chickens based on posture changes, achieving 99.469% accuracy with SVM. Okinda et al. identified Newcastle disease in chickens using posture shape features, achieving 98.8% accuracy with SVM. Deep learning methods like Improved Feature Fusion Single Shot

MultiBox Detector have also been proposed for automated poultry posture recognition, achieving high precision in detecting and classifying different postures for efficient flock management.

4. CONCLUSIONS

Disease control in poultry farming is challenging due to scale and manual inspection limitations. Automatic disease detection using clinical symptoms like sound, temperature, and activity is crucial for real-time monitoring. Methods include machine vision, sound recording, and wearable sensors, each with pros and cons. Additional symptoms like cockscomb abnormalities and feather changes are also key indicators. Future advancements aim to integrate these into comprehensive databases and develop intelligent monitoring systems to improve farm management, disease control, and overall sustainability.

REFERENECES

[1] Wael Mohamed Elmessery, Joaquín Gutiérrez, Gomaa, Ibrahim Elkhaiat, El-Soaly, I. S., Alhag, S. K., Al-Shuraym, L. A., Akela, M. A., Moghanm, F. S., &Abdelshafie, M. F. (2023). YOLO-Based Model for Automatic Detection of Broiler Pathological Phenomena through Visual and Thermal Images in Intensive Poultry Houses. Agriculture, 13(8), 1527–1527. https://doi.org/10.3390/agriculture13081527

[2] Cui, Y., Kong, X., Chen, C., & Li, Y. (2023). Research on broiler health status recognition method based on improved YOLOv5. Smart Agricultural Technology, 6, 100324–100324. https://doi.org/10.1016/j.atech.2023.100324

[3] Nasiri, A., Amirivojdan, A., Zhao, Y., &Gan, H. (2024). An automated video action recognition-based system for drinking time estimation of individual broilers. Smart Agricultural Technology, 7, 100409–100409. https://doi.org/10.1016/j.atech.2024.100409

[4] Raul Hector Marin, Jorge Martin Caliva, &Jackelyn Melissa Kembro. (2024). Dynamics of changes in broiler spatial distribution induced by a robot with autonomous navigation along the growing cycle. Poultry Science, 103(6), 103710–103710. https://doi.org/10.1016/j.psj.2024.103710

[5] Guo, Y., Regmi, P., Ding, Y., Bist, R. B., & Chai, L. (2023). Automatic detection of brown hens in cage-free houses with deep learning methods. Poultry Science, 102(8), 102784. https://doi.org/10.1016/j.psj.2023.102784

[6] Mar Ariza-Sentís, Vélez, S., Martínez-Peña, R., Baja, H., & Valente, J. (2024). Object detection and tracking in Precision Farming: a systematic review. Computers and Electronics in Agriculture, 219, 108757–108757. https://doi.org/10.1016/j.compag.2024.108757

[7] Wang, L., Chen, W., Yang, W., Bi, F., & Yu, F. R. (2020). A State-of-the-Art Review on Image Synthesis With Generative Adversarial Networks. IEEE Access, 8, 63514–63537. https://doi.org/10.1109/ACCESS.2020.2982224

[8] Castro, F. L. S., Chai, L., Arango, J., Owens, C. M., Smith, P. A., Reichelt, S., DuBois, C., &Menconi, A. (2022). Poultry industry paradigms: connecting the dots. Journal of Applied Poultry Research, 32(1), 100310. https://doi.org/10.1016/j.japr.2022.100310

[9] Fasina, Y. O., Suarez, D. L., Ritter, G. D., Gerken, E. C., Farnell, Y. Z., Wolfenden, R., & Hargis, B. (2024). Unraveling Frontiers in Poultry Health (Part 1) – Mitigating economically important viral and bacterial diseases in commercial Chicken and Turkey production. Poultry Science, 103500–103500. https://doi.org/10.1016/j.psj.2024.103500

[10] Glisson. (1998). Bacterial respiratory disease of poultry. Poultry Science, 77(8), 1139–1142. https://doi.org/10.1093/ps/77.8.1139

[11] Yan, Jianqi, et al. “Enhanced Object Detection in Pediatric Bronchoscopy Images Using YOLO-Based Algorithms with CBAM Attention Mechanism.” Heliyon, vol. 10, no. 12, 1 June 2024, pp. e32678–e32678, https://doi.org/10.1016/j.heliyon.2024.e32678. Accessed 8 July 2024.

[12] Wu, J.P.; Yang, Y.F.; Cheng, L.; Wu, J.; Xi, L.L.; Ma, Y.; Zhang, P.Y.; Xu, X.Y.; Zhang, D.K.; Li, S.Y. GCdiscrimination: Identification of gastric cancer based on a milliliter of blood. Brief Bioinform. 2021, 22, 536–544.

[13] Stergiou, G.; Kollias, A.; Parati, G.; O’Brien, E. Office Blood Pressure Measurement The Weak Cornerstone of Hypertension Diagnosis. Hypertension 2018, 71, 813–815.

[14] Liu, W.; Tao, Z.W.; Wang, L.; Yuan, M.L.; Liu, K.; Zhou, L.; Wei, S.; Deng, Y.; Liu, J.; Liu, H.G.; et al. Analysis of factors associated with disease outcomes in hospitalized patients with 2019 novel coronavirus disease. Chin. Med. J. 2020, 133, 1032–1038.

[15] Carpentier, L.; Berckmans, D.; Youssef, A.; Berckmans, D.; van Waterschoot, T.; Johnston, D.; Ferguson, N.; Earley, B.; Fontana, I.; Tullo, E.; et al. Automatic cough detection for bovine respiratory disease in a calf house. Biosyst. Eng. 2018, 173, 45–56.

[16] Aziz, N.A.; Bin Othman, M.F. Binary Classification using SVM for Sick and Healthy Chicken based on Chicken's Excrement Image. Pertanika J. Sci. Technol. 2017, 25, 315–324.

[17] Li, X.H.; Nie, C.S.; Liu, Y.C.; Chen, Y.; Lv, X.Z.; Wang, L.; Zhang, J.W.; Yang, W.F.; Li, K.Y.; Zheng, C.W.; et al. The Genetic Architecture of Early Body Temperature and Its Correlation With Salmonella Pullorum Resistance in Three Chicken Breeds. Front. Genet. 2020, 10, 1287. [CrossRef]

[18] Manteuffel, G.; Puppe, B.; Schön, P.C. Vocalization of farm animals as a measure of welfare. Appl. Anim. Behav. Sci. 2004, 88, 163–182. [CrossRef]

[19] Du, X.D.; Carpentier, L.; Teng, G.H.; Liu, M.L.; Wang, C.Y.; Norton, T. Assessment of Laying Hens' Thermal Comfort Using Sound Technology. Sensors 2020, 20, 473. [CrossRef] [PubMed]

[20] Fontana, I.; Tullo, E.; Butterworth, A.; Guarino, M. An innovative approach to predict the growth in intensive poultry farming. Comput. Electron. Agric. 2015, 119, 178–183.

[21] Aydin, A.; Berckmans, D. Using sound technology to automatically detect the short-term feeding behaviours of broiler chickens. Comput. Electron. Agric. 2016, 121, 25–31.

[22] Gonzalez, J.J.; Nasirahmadi, A.; Knierim, U. Automatically Detected Pecking Activity in Group-Housed Turkeys. Animals 2020, 10, 2034.

[23] Nasirahmadi, A.; Gonzalez, J.; Sturm, B.; Hensel, O.; Knierim, U. Pecking activity detection in group-housed turkeys using acoustic data and a deep learning technique. Biosyst. Eng. 2020, 194, 40–48.

[24] Yang, J.; Shen, M.X.; Liu, L.S.; Lu, M.S.; He, C.L.; Li, J.W. Research of detection method for broiler chicken feed intake based on audio technology. J. South China Agric. Univ. 2018, 39, 118–124.