Poultry disease early detection methods using deep learning technology

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ABSTRACT

Poultry production is a pivotal contributor to global economic growth, playing a central role in promoting human ecosystem sustainability. It offers affordable and readily accessible protein sources, encompassing meat, eggs, and other by-products. Beyond its direct nutritional benefits, poultry production enhances household income, bolsters food security, and aids in poverty reduction, making it integral to worldwide economic advancement. However, as the global population surges, so does the demand for poultry meat and eggs. Concurrently, poultry disease management emerges as a paramount challenge, leading to significant threats to food security and economic stability. Leveraging cutting-edge technology offers promising avenues to devise strategies that not only bolster farm profitability but also mitigate environmental impacts and foster the well-being of both animals and humans. This study systematically reviews the latest literature concerning poultry disease diagnosis based on deep learning techniques, elucidating the clinical manifestations associated with various ailments. The analysis indicates that emerging technological solutions, especially image processing and deep learning (DL), substantially outperform conventional manual inspection methods in early disease detection and warning in the poultry sector. Such innovations underscore their potential for revolutionizing poultry health management and disease mitigation.

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1. INTRODUCTION

The poultry industry plays a critical role in global economic development. It contributes to socioeconomic growth by providing people with affluent protein and nutrition [1]. The development of agriculture is the foundation of a country's economic progress. Humans consume a substantial amount of meat and eggs produced by the poultry industry [2]. Worldwide affluence and population growth fuel food demand, resulting in increased poultry production in numerous nations. By 2030, it is estimated that the global population will reach 8.6 billion, posing a significant challenge to adequate meat production and provision [3]. It is estimated that 40% of poultry meat and egg demand will increase by 2050 [4]. Poultry meat and eggs are essential to human life because they are a cost-effective and valuable protein source in the daily diet. Poultry farming is also a direct source of family income for many local farmers. Due to its small size and low investment, the small-scale poultry feeding industry is a reliable source of employment and family income for a variety of households [5]. It is imperative to maintain sustainable food production and livelihoods at multiple scales to achieve sustainable development goals. While a substantial industry opportunity arises from increasing poultry demand, concurrent challenges persist. As climate change, land erosion, biodiversity loss, and biosecurity threats increase, concerns about human health and animal protein have intensified and are being focused on. As long-term environmental changes occur, new demands, challenges, and pressures are arising as well [6]. The poultry farming industry is susceptible to a number of diseases, including avian influenza, Salmonellosis, fowl cholera, Newcastle, and Coccidiosis [7]–[13]. Figure 1 describes poultry diseases' transmission routes and clinical manifestations.

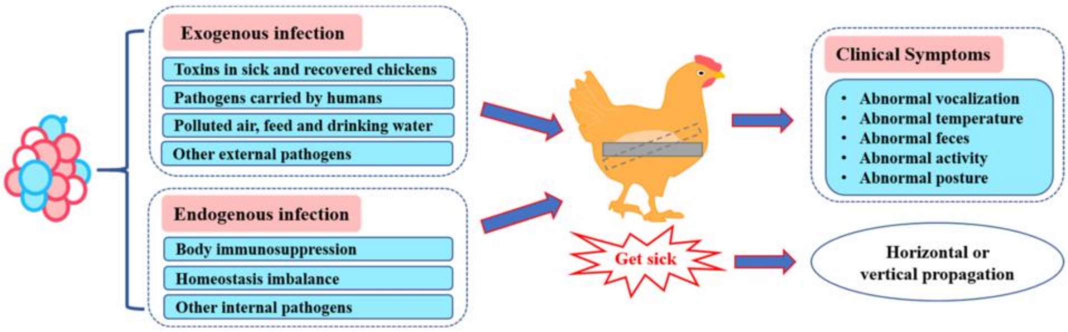

Figure 1. The routes of poultry diseases transmission and clinical manifestations [2]

Influenza affects not only the quantity of poultry meat and eggs produced but also their quality, which are typically significant effects of avian influenza. Additionally, birds have been observed to suffer from a high rate of morbidity and mortality. It is common for avian influenza to be transmitted through feces, the mouth, or aerosol [8]. Several clinical signs may be observed, such as dehydration, loss of appetite, fever, depression, decreased intake of food and water, a decrease in response to stimuli, wing paralysis, torticollis, and tremors [9]. So, it is paramount to adopt a mechanism for early avian influenza infection identification before outbreaks. Salmonellosis is another one of the most widespread bacterial zoonotic diseases, with around 155,000 deaths observed around the world. In the poultry industry, it is one of the most prevalent diseases, which is caused by varieties of Salmonella. Salmonellosis could be transmitted not only through the horizontal fecal-oral pathway but via vertically embrocated eggs as well. It is common for mature poultry to exhibit decreased egg production, fertility, and hatchability, as well as anorexia, diarrhea with white or yellow mucus, and watery mucosa [10]. Salmonellosis could be spread in poultry farms through infected sick chickens, contaminated equipment, water and feed, domestic animals, and the surrounding environment as well. Fowl cholera is a kind of bacterial-infected disease in poultry farming. Fowl cholera is a septicemic disease affecting wild and domestic birds. Mature poultry are more susceptible to infection than young ones.

The transmission route for poultry cholera can be oral, nasal discharge, or feces. Some typical clinical symptoms include nasal discharge, respiratory rales, and coughing [1]. At the same time, as the joints continue to swell and deform, some inflammatory substances leak out, ultimately leading to necrosis [11]. Apart from that, clinical symptoms like ruffled feathers, mucous discharge from the mouth and nose, diarrhea, and general depression are addressed as well [12]. Newcastle disease is a viral poultry disease. A group of viruses closely related to the avian paramyxovirus type 1 serotype causes Newcastle disease. In poultry farming, it is one of the most feared diseases and one of the leading causes of mortality. Some clinical signs, such as respiratory and nervous symptoms. Oral is the most common transmission route, but respiratory and conjunctival modes may also be included [13]. Newcastle disease is characterized by a variety of major symptoms including coughing, gasping, greenish diarrhea, sneezing, cyanosis of the comb and wattle, corticoids, paralysis (wings and legs), tremors, and a twisted neck. Ducks and geese have stronger immune systems than chickens and turkeys against this disease. As with pathogenic avian influenza, Newcastle disease presents very similar clinical symptoms. Early isolation of virus-infected poultry is the most effective countermeasure [14]. Coccidiosis is a parasitic disease in poultry farming. A protozoal parasite causes this disease, making it one of the most prevalent diseases in poultry. Some clinical symptoms include poor growth, feed conversion, and even death under severe conditions. Furthermore, parasites could decrease herd immunity to other diseases [1].

Most poultry diseases are characterized by ruffled feathers, depression, panting, diarrhea (watery or bloody), drooling saliva, coughing, head and eye swelling, curling of the head and neck, and decreased egg production. Based on the above clinical symptoms, sick poultry could be diagnosed by vocalization, body temperature, feces, and daily behaviors, allowing for health evaluation [2]. Handling sick poultry cautiously and keeping normal poultry away from potentially ill ones in time is critical in poultry farming, especially in large-scale farming. So, timely isolating the symptoms-appearing chickens could prevent healthy chickens from getting infected [15].

To combat disease in poultry farms, prevention, vaccines, and medications are the commonly used mechanisms to enhance health conditions and overall production [16]. Poultry industry production could be enhanced with the appropriate strategies for husbandry management and clean feeding environments. Traditional methods involve veterinarians conducting manual observation or biochemical testing, which are time-consuming and labor-intensive. Biochemical tests are sensitive but expensive, and manual inspection could result in incorrect results. Moreover, traditional inspection methods may miss the appropriate time for disease treatment, especially in cases of severe infectious diseases. With the modern technology development, internet of things (IoT) applications, video and image processing, classification capabilities, and smart poultry management have been emphasized in recent years [17]–[20]. The low cost of computing resources and common algorithms make contemporary technology an indispensable tool for monitoring vast farms and increasing production [21]. Advanced technological solutions are crucial for poultry farm health management, as poultry meat and eggs are the largest protein sources [22]. Disease monitoring and early detection are essential for decreasing poultry morbidity and mortality and boosting production yields. By deploying modern technologies, sick poultry early identification and warning could be automatically and consistently controlled. It aims to reduce infection rates by isolating sick poultry in a timely manner.

Nowadays, deep learning technology has the capability of self-learning to analyze images automatically, which enables the constructed deep learning model to facilitate the analysis and management of the poultry farming industry, especially in sick poultry early detection. Powered artificial intelligence (AI) and deep learning technologies could be deployed into the data analysis process to analyze, predict, and inform end-users of abnormal conditions to reduce the spread of poultry diseases and ensure biosecurity. The application of big data presents an unprecedented opportunity in the development of tools that will optimize farm profitability, reduce environmental impact, and increase the health and welfare of animals and humans [23]. To improve animal health and reduce losses, it is imperative to detect abnormalities in poultry and issue early warnings of infectious diseases. Nevertheless, inadequate methods could result in decreased productivity and extensive mortality. Symptom detection technologies could continuously, noninvasively, and automatically monitor the health conditions of laying hens and broilers, which could aid in making early disease warning decisions. However, clinical symptom-based monitoring systems for on-farm disease detection have not been fully implemented [2].

All the references selected for this project are collected from the Google Scholar and Web of Science databases. A collection of searching keywords is used to find suitable references: "Poultry/chicken disease/behavior/posture detection/monitoring/warning", "Deep/machine learning", "Smart/intelligent poultry farm" and similar words. There are several criteria set to include the specific reference: i) the study mentions at least one method to diagnose the disease based on poultry disease clinics in detail; ii) the proposed methodology is related to machine learning or deep learning algorithms; and iii) the proposed system is constructed and experimented with. Based on the above conditions, the related references are selected. A review and summary of these references are used to provide an in-depth understanding of the application based on deep learning techniques in the early diagnosis of poultry diseases, making a significant contribution to this research.

2. LITERATURE REVIEW

Poultry's physiological traits include rich information about their environmental condition, emotional state, and health status. This information can be used to monitor the welfare of poultry and inform decisions about husbandry practices. Studies have shown that physiological traits could be used to detect changes in the environment and animal health. In poultry, some common physiological traits like body temperature, vocalization, and feces are associated with different diseases [24]. So, these factors are utilized and measured to detect and diagnose diseases in their early stages to avoid potential risks.

2.1. Abnormal body temperature

Poultry is a homeothermic animal that creates and distributes heat to keep core and skin surface temperatures constant. This is called homeothermy, and it assists poultry in regulating its metabolism and improving its physiological functions. Homeothermy improves the bird's capacity to obtain food and thrive in a variety of situations [25]. The poultry industry faces significant economic losses due to heat stress (HS), which affects production performance, body temperature, and immune responses. One of the most important ways to identify HS possessions in poultry is to monitor their body temperature during rearing and take action in time [26]. The temperature would change according to different pathological or stress conditions, such as disease infection or an instinctive response. Therefore, temperature change could be one significant factor that indicates early warning for sick poultry. High temperatures decrease feed efficiency, body weight, feed consumption, and egg production, increasing mortality and pathological damage [27]. The temperature of the animal body is intimately associated with metabolism and living activities, and it reflects their physiological and health status. Infrared thermography (IRT) technology is a type of non-invasive monitoring technique used to assess animal health and physiological changes. IRT has been used in animal temperature detection for disease detection, extreme thermoregulation, and estrus detection [28]. It is possible to determine poultry surface temperatures using infrared cameras. This is done by creating images displayed in different colors corresponding to different temperatures using imaging techniques. Chicken body temperature can be measured by applying this technology after changes in diet, stress levels, and environmental conditions [23]. Noh *et al.* [29] developed an innovative system for real-time surveillance of infected poultry before disease manifestation. It showed if it would be possible to employ thermal imaging to find changes in the surface temperature of ducks and chickens as an early sign of highly pathogenic avian influenza (HPAI) infection. Thermal camera footage was used to detect H5N1 infections in chickens and ducks. The paper suggested using thermal imaging cameras in livestock to detect early signs of the avian influenza virus. It also suggested a maximum change in surface temperature that should be considered when deciding to kill infected birds. Chuang *et al.* [30] proposed a goose surface temperature monitoring system for commercial poultry houses. It developed a deep learning model to automatically identify geese in visible images and automatically determine individual goose surface temperatures based on infrared (IR) thermal images. This model used convolutional neural networks (CNNs) to find geese in visible images and a second CNN to figure out the surface temperature by looking at the IR thermal images of the geese. By using both visible images and infrared data, the model can accurately classify the geese and figure out their surface temperature.

2.2. Abnormal vocalization

Recognizing and diagnosing illnesses in chickens is critical for the health and well-being of poultry flocks. Visual observation and physical examination have traditionally been the primary methods used to identify sick chickens. However, new research suggests that abnormal vocalizations emitted by sick chickens could serve as a potential indicator of their health status. Figure 2 describes the different time domain characteristics of chickens: healthy, infected Newcastle, bronchitis virus, and avian influenza. Another way to detect illnesses in chickens is by analyzing their vocalizations for abnormal patterns and characteristics using voice recognition technology [31].

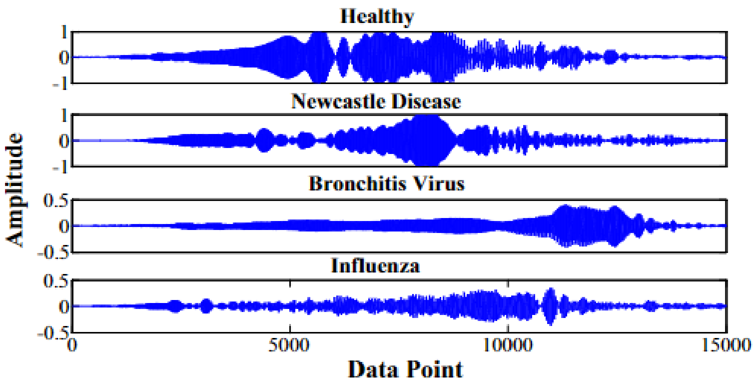

Figure 2. Four time domain signal characteristics [32]

Abnormal voice detection is another way to identify sick poultry in the early stages. This novel approach has the potential to supplement existing diagnostic methods by providing a non-invasive and efficient method of early illness detection on poultry farms. Quintana *et al.* [33] have developed a hybrid solar-powered chicken disease monitoring system using decision tree models for disease identification and verification. The system used visual and acoustic inputs from 15 chicken samples, identifying six symptoms. After 72 hours of continuous monitoring, the learning model achieved 84.6% accuracy in classifying diseased chickens when visual imagery was considered, and 86.1% accuracy when audio inputs were provided. Li *et al.* [34] presented a sex detection system based on chick calls for poultry breeding. This system aimed to achieve chick-call classification and sex detection using the proposed deep learning methods. The experiment studied three different chick breeds and used a short-time and zero-crossing rate to identify the chick call endpoints in audio.

The results showed that the ResNet-50 deep neural network (DNN) had 83% highest test accuracy for three-yellow chicks, 76.8% for native chicks, and 66.56% for flaxen-yellow chick calls. The gated recurrent unit (GRU) and convolutional recurrent neural network (CRNN) networks achieved the highest sex identification accuracy of 90% and 80%, respectively. Newcastle disease is a prevalent poultry disease affecting health and production. A novel ResNet50-based system, the deep poultry vocalization network (DPVN), was proposed for early identification using poultry vocalization. To reduce the influence of noise on the signal, the method combined multi-window spectral subtraction and high-pass filtering. The proposed identification system attained an average accuracy of 91.06% for infected chicks within the first, second, third, and fourth days. A valuable benefit of this method was the improvement of animal welfare and poultry production through automatic monitoring [35]. Jakovljević *et al.* [36] introduced an audio-based system to monitor broiler chicken stress. It was based on audio signals from the first few weeks in a chicken's life to detect stress. The system was developed to monitor the sound of birds' vocalizations during their early life stages. By monitoring these sounds, the system could accurately detect stress and could be used to improve the conditions in which chickens are raised. It showed that pre-recorded chicken sounds could be used with different classifiers to figure out if a chicken was stressed or not. Each classifier in the system classes adult chickens into a different category depending on the audio data. Four classifiers were tested at the 1,000 ms frame level, and the accuracy of these classifiers varies from 63% to 83%, depending on the age group. Wang *et al*. [37] proposed an effective audio-based system for automatically identifying and recognizing the different types of chick vocalizations, including begging, peeping, and chirping.

The system used a deep learning algorithm to analyze audio recordings of chick vocalizations and identify specific features that are associated with each type of vocalization. This allows the system to accurately identify and recognize the different types of vocalizations. A new feature extraction method was used based on joint time-frequency scattering (JTFS) transformations; varying chick calls can be distinguished 10% more accurately. Carpentier *et al.* [38] developed an algorithm to detect chicken sneezing sounds in noisy environments. The algorithm was developed using a dataset of 763 sneezes from 51 chickens. The algorithm categorized the sounds as sneeze or non-sneeze, with 66.7% sensitivity and 88.4% precision. This work marked the first step towards an automated, sound-based detection system for poultry health. Huang *et al.* [39] presented a new audio analysis-based detection method for the early detection of avian influenza using chicken sound and ambient noise. The extracted sound is processed using Mel-frequency cepstral coefficients (MFCC) to differentiate between healthy and infected chickens. The method's accuracy ranges from 84% to 90%, demonstrating the potential for efficient detection in large-scale poultry farming.

2.3. Abnormal dropping

When poultry are infected with pathogens, their droppings may appear differently. The characteristics of chicken excrement are different between healthy and sick chickens. Different from typical healthy feces. Diarrhea that is liquid or watery feces that are orange or red (bloody), black, dark green, yellow, watery white, foamy, oily, or contain worms can be an indication of diseases or parasites [40]. Figure 3 describes the feces traits related to corresponding chicken diseases. So, chicken droppings are one of the most significant signals to indicate their health conditions.

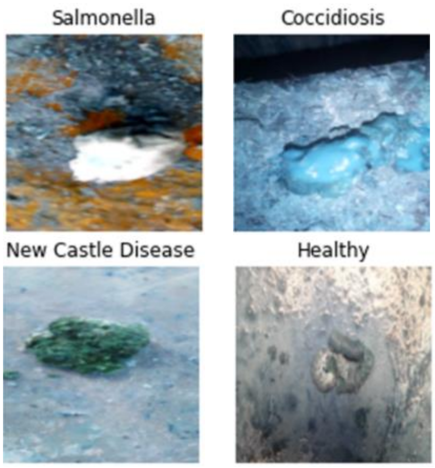

Figure 3. Feces characteristics associated with different chicken diseases [41]

The excretion status of livestock and poultry is crucial for monitoring their health. Inspectors currently make preliminary judgments by observing the color and traits of feces on the manure belt. The identification of feces from poultry is critical for food safety and disease prevention. Fluorescence imaging could detect excrement, but it requires skill. Using fluorescence imaging and deep learning approaches, the study recognized disease-associated feces types from feces photos. EfficientNet-B0 had an accuracy of 97.32% in segmenting feces, while U-Net had an accuracy of 89.34% [42]. Zhu and Zhou [43] proposed a machine vision-based chicken manure image recognition method for online monitoring. The method preprocessed the collected images, made preliminary judgments about abnormal manure, and analyzed grayscale characteristics to determine normality. The method was effective for monitoring images of abnormal chicken droppings and can initially determine the health condition of chickens. Fecal imaging is essential for determining the health of poultry, but producers frequently struggle with disease diagnosis. Aworinde *et al.* [44] developed a dataset of images of healthy and ill feces from poultry farms in Nigeria. The dataset comprises 14,618 labeled images that can be utilized in machine learning models and computer vision applications. This dataset was designed to assist farmers and agricultural extension agents in managing poultry farms, minimizing losses, maximizing profit, and maximizing protein sources.

Mbelwa *et al.* [45] proposed a chicken feces classification system using a CNN deep learning solution. The XceptionNet model outperforms other models in all metrics, with a 94% validation accuracy using pretraining. The fully trained CNN comes in second, while the pre-trained XceptionNet method has the highest prediction accuracy, making it suitable for chicken disease detection applications. Due to late diagnoses and a dearth of credible specialists, diagnostic methods for chickens, such as oocyte count, virus detection, and polymerase chain reaction (PCR), are frequently inadequate. Suthagar *et al.* [46] proposed a model for the early detection and classification of poultry diseases using a database based on feces. The dataset consists of 6,812 images divided into four categories: healthy chicken, Coccidiosis, Salmonella, and Newcastle. Deep learning techniques, such as pre-trained DenseNet, Inception, and MobileNet, accurately predict chicken feces with 97% accuracy, making them appropriate for use in poultry diagnostic applications. Widyawati and Gunawan [47] presented a study conducted to detect early-sick chickens on a real poultry farm in Indonesia using the YOLOv5 algorithm. This study was carried out through the analysis of chicken feces' image features. The results of this research achieved 89.2% accuracy.

2.4. Early disease detection through behavioral characteristics

Early disease detection is a critical aspect of effective poultry health management, as it enables prompt intervention and inhibits the spread of illness within flocks. While traditional diagnostic methods rely on physiological and laboratory-based indicators, emerging research suggests that behavioral characteristics could serve as an additional factor for identifying sick poultry. By closely monitoring their behavior and recognizing abnormal patterns, such as changes in feeding habits, reduced activity levels, or abnormal body pose characteristics, it may be possible to detect early indicators of illness in poultry [48]. Figure 4 shows the behaviors of normal and sick chickens [49].

This innovative approach of using behavior identification as a tool for early disease detection holds significant potential for enhancing poultry health surveillance and allowing for prompt intervention, ultimately safeguarding the welfare and productivity of chicken populations. Animal behavioral analysis is becoming increasingly important for farm animal welfare, health, efficiency, and sustainable environments. Behavioral analysis can help identify poultry diseases through accurate pose estimation, which can help farmers diagnose or isolate sick poultry. Hilmi *et al.* [50] studied the use of deep convolutional networks (DeepCNN) to accurately detect poultry's body key points in videos, allowing for the development of an automated poultry health classifier. The paper explained the data gathering and tuning and compared the best available DeepCNN using DeepLabCut, a pose estimation toolbox. Poultry pose estimation is critical for assessing abnormal behavior and predicting sickness in poultry.

Fang *et al.* [51] developed a DNN approach and compared it with other techniques for estimating the posture of individual chickens. The approach has a high precision of 95%, facilitating abnormal behavior detection in poultry. Fang *et al.* [52] used DNN pose estimation and a Naive Bayesian model (NBM) to analyze broiler chicken behavior. The method identified chickens in walking, standing, eating, running, preening, and resting states, as shown in Figure 5, with a precision of 0.7511 for standing, 0.5135 for walking, 0.6270 for running, 0.9361 for eating, 0.9623 for resting, and 0.9258 for preening.

This non-invasive method offered valuable insights for future behavior analysis to identify sick chickens in broiler chicken farming. Poultry behavior is critical for health and well-being, and grill producers must detect lameness early. Using video data, Nasiri *et al.* [53] built a position estimation-based model to detect lameness in broilers. DeepCNN were used to recognize seven important spots on walking broilers, which were then fed into a long short-term memory (LSTM) model. The model has 95% overall classification accuracy and 97.5% average per-class classification accuracy, making it an effective and non-invasive tool for chicken farms. Xie and Chang [54] presented a method for classifying broiler behaviors by using object detection and recurrent-based DNNs. The YoLov4 object detection model was trained and used to detect five pre-defined parts of a broiler chicken, and then the corresponding chicken skeleton was constructed from these identified parts.

Figure 4. Samples of sick and normal chickens. From left to right, the labels are normal chickens, chickens with chicken head disease, and chickens with ILT, Newscalte, and Marek diseases [49]

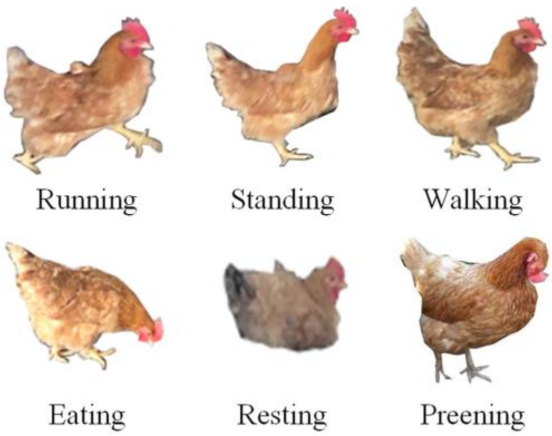

Figure 5. Typical chicken behaviors [52]

The angle between backbone fulcrum vectors was extracted. Six broiler behaviors were detected using a time-series-based LSTM network. The scheme was validated in an outdoor environment, with average precision, recall, and F1-score of 82%, 81%, and 81%, respectively. Using broilers as an example, Zhang and Chen [55] proposed an autonomous detection method for unwell chickens. To improve the network structure and adapt to varied recognition situations, the system employed the ResNet residual network. The model's identification rate on the test set improved by 2.1% after tens of thousands of recurrent training sessions, resulting in a 93.7% recognition rate. This intelligent management platform focused on remote monitoring of cattle and poultry breeding conditions, dealing with behavioral physiology, and tracking production performance. A camera-based system was developed to monitor flocks and detect injuries using neural networks.

A preliminary study used manually annotated 244 images of turkeys to train a neural network called HRNet-W48 for injury detection. Seven turkey key points were defined. The proposed model achieved an average accuracy of 73.5%, and showed positive influences on turkey management, allowing for clear differentiation between individual animals even in crowded situations [56]. Bakar *et al.* [57] developed a supervised machine learning algorithm for early detection of bacteria- or virus-infected chickens using the International Commission on Illumination (CIE) XYZ color space. The algorithm uses a logistic regression model to classify chickens, revealing 100% sensitivity and 83% specificity. The comb chromaticity of infected chickens' changes from red to green, contributing to the development of modern technology in agriculture applications. The detection method feature serves as an indicator for detecting bacteria or virus-infected chickens, contributing to the advancement of modern technology in agriculture applications shown in Table 1, it is summarizes various early detection methods associated with poultry diseases.

Table 1. Summarization of poultry abnormality detection methods

Author	Year	Reference	Discussion	Results
Noh *et al*.	2021	[29]	Developed a real-time surveillance system for poultry surface temperature monitoring based on a thermal camera.	Suggested using thermal imaging cameras in livestock to detect early signs of the avian influenza virus.
Chuang *et al*.	2021	[30]	Proposed a goose surface temperature monitoring system based on a CNN algorithm.	An infrared thermal camera combined with a CNN model could detect individual surface temperature changes accurately.
Quintana *et al.*	2022	[33]	Developed a hybrid solar-powered chicken disease monitoring system using decision tree models for disease identification and verification based on various audios.	The proposed model achieved up to 86.1% accuracy in classifying diseases.
Jakovljević *et al.*	2019	[36]	Introduced an audio-based system to monitor broiler chicken stress using support vector machines (SVM) algorithm.	The system achieved a range of 63%–83% accuracy.
Carpentier *et al.*	2019	[38]	Developed an algorithm to monitor chicken sneezing sounds in noisy environments.	Achieved a precision of 88.4%.
Huang *et al.*	2019	[39]	Presented an audio-based detection method for the early detection of avian influenza based on MFCC method.	Achieved up to 90% accuracy.
Gorji *et al*.	2022	[42]	Demostration of using fluorescence imaging and deep learning approaches to recognize poultry feces.	Achieved up to 97% accuracy.
Mbelwa *et al.*	2021	[45]	Proposed a CNN-based solution to predict chicken feces' classification.	Achieved a 94% validation accuracy.
Suthagar *et al.*	2023	[46]	Proposed a feces-based deep learning model for the early detection and classification of poultry diseases.	Achieved up to 97% accuracy.
Widyawati and Gunawan	2022	[47]	Presented a feces-based model to detect early sick chickens using YOLO V5 algorithm.	Achieved 89.2% accuracy.
hilmi *et al*.	2022	[50]	Developed ResNet-based pose estimation toolbox to detect poultry's body keypoints.	Poultry pose estimation is critical for assessing abnormal behavior and predicting sickness in poultry.
Fang *et al*.	2022	[51]	Developed a DNN approach to estimate the posture of individual chickens.	Achieved 95% accuracy.
Fang *et al.*	2021	[52]	Developed a DNN pose estimation model to analyze chicken behavior.	Achieved 78.64% average precision.
Xie and Chang	2022	[54]	Presented a method for identifying broiler behavior based on YOLO v4 algorithm.	Achieved 82% accuracy.
Gourisaria *et al.*	2023	[58]	Proposed a CNN-based model called ChicNetV6 to classify different diseases.	Achieved 94.49% accuracy.
Yang *et al*.	2023	[59]	Developed a CNN-based model to classify six chicken behaviors.	Achieved 95.3% average accuracy.

Gourisaria *et al.* [58] utilized CNN models to classify diseases like Salmonella, Coccidiosis, Healthy, and NewCastle disease. A six-behavioral classifier was developed to monitor natural behaviors in cage-free birds, including feeding, drinking, walking, perching, dust bathing, and nesting. The classifier achieved an average accuracy of 95.3%, with the highest accuracy for drinking behavior in chicks (97.8%) and 92.5% for nesting behavior. The classifier is useful for separating cage-free bird behaviors across various life periods and environments [59]. Based on the identified behaviors, the activities of monitored poultry could be further analyzed. For example, if walking and drinking activities were reduced, individuals would be most susceptible to pathogens and might already be infected [60].

3. DISCUSSION

In the domain of poultry farming, effective disease control remains a paramount concern. Conventional management methodologies, though human-resource intensive, often fail to meet the escalating demands of contemporary poultry operations, particularly in large-scale establishments where manual inspection approaches are subjective and labor-intensive. The integration of modern technologies, such as AI and deep learning, CNN, in particular, have achieved outstanding results in image classification tasks. This provides possibilities for the health management of poultry and the automatic analysis of poultry diseases. It promises to augment the efficiency of poultry farming by facilitating automated health management and real-time early disease detection based on clinical indicators. While the convergence of human expertise and AI in the livestock sector does present nuanced challenges, the accrued benefits appear to significantly overshadow these concerns. Current deep learning techniques, characterized by their inherent self-learning capabilities, have demonstrated proficiency in diverse poultry management scenarios, notably in early disease detection. Utilizing computer vision technology in livestock welfare and health management research streamlines continuous poultry observation, making it more efficient. The synergy between computer vision and deep learning is poised to transform conventional poultry farming practices, making them more modern and high-production.

Currently, a myriad of non-invasive early poultry disease detection techniques, such as abnormal vocal pattern analysis, dermal temperature assessment, fecal analysis, postural estimation, and behavior monitoring, are the subjects of extensive global research. These non-invasive diagnostic methods do not cause stressful effects on the poultry and ensure the normal habits of the poultry. Beyond mitigating large-scale disease outbreaks, these innovations have the potential for broader applications in extensive animal-rearing contexts, including traditional poultry farming. In this way, farmers can take precautions in advance to minimize the impact of diseases. Despite the great potential of deep learning technology, there are still challenges in applying it in the field of poultry farming. First, a large amount of labeled data is needed for model training. In addition, the actual farming environment may affect the accuracy of the sensor data. Economics also needs to be considered, i.e., whether the cost of collecting and processing the data can be offset by the profitability of the farming industry.

4. CONCLUSION

Poultry diseases pose formidable threats to both small-scale and industrial-scale farming practices. Conventional manual inspection methods, while foundational, have become labor-intensive and often fall short in addressing the demands precipitated by the escalation of poultry populations and the expansion of farming scales. Leveraging contemporary technology, it's feasible to develop a method that provides real-time, non-invasive, and efficient health monitoring for poultry, facilitating automated disease detection and immediate intervention alerts. Current advancements in intelligent poultry health monitoring predominantly employ metrics such as dermal temperature variations, vocalization traits, fecal characteristics, posture, and specific behavioral characteristics. The integration of AI and advanced sensing technologies promises to elevate operational efficiencies and commercial prospects for farmers, while also advancing the welfare of both animals and the humans involved. The future development trend of the poultry sector seems to be steering toward more intelligent management and automatic health monitoring systems. A sophisticated remote monitoring mechanism promises continuous and automated oversight, with a focus not just on the environmental conditions but also on the holistic health of the poultry. By deploying an intelligent early warning system for poultry diseases, there is potential to drastically diminish the reliance on manual monitoring, enhance the overall health of poultry, streamline production processes, and boost profitability. By capitalizing on the robust computational capabilities of deep learning, it becomes possible to undertake real-time data analysis. Should any discrepancies or unusual patterns in health data arise, farm managers are promptly alerted, ensuring proactive measures are instituted to thwart potential disease outbreaks. For a more precise analysis, it is imperative to encompass a comprehensive understanding of the multifaceted attributes associated with the disease in question.

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