Research Progress in the Early Warning of Chicken Diseases by Monitoring Clinical Symptoms

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Abstract: Global animal protein consumption has been steadily increasing as a result of population growth and the increasing demand for nutritious diets. The poultry industry provides a large portion of meat and eggs for human consumption. The early detection and warning of poultry infectious diseases play a critical role in the poultry breeding and production systems, improving animal welfare and reducing losses. However, inadequate methods for the early detection and prevention of infectious diseases in poultry farms sometimes fail to prevent decreased productivity and even widespread mortality. The health status of poultry is often reflected by its individual physiological, physical and behavioral clinical symptoms, such as higher body temperature resulting from fever, abnormal vocalization caused by respiratory disease and abnormal behaviors due to pathogenic infection. Therefore, the use of technologies for symptom detection can monitor the health status of broilers and laying hens in a continuous, noninvasive and automated way, and potentially assist in the early warning decision-making process. This review summarized recent literature on poultry disease detection and highlighted clinical symptom-monitoring technologies for sick poultry. The review concluded that current technologies are already showing their superiority to manual inspection, but the clinical symptom-based monitoring systems have not been fully utilized for on-farm early detection.

Keywords: clinical symptoms; disease warning; automatic monitoring; physiological characteristics; behavioral characteristics

1. Introduction

The poultry industry provides an abundance of low-cost, high-quality protein products for human consumption, plays an increasingly important role in the global economy and is the fastest-growing agricultural sub-sector [1]. In 2018, more than 68 billion chickens were raised globally, accounting for one-third of global meat production, with an additional 1.38 trillion eggs available for human consumption [2], which to a certain extent guaranteed food safety.

With an increase in the population and improvements in quality of life worldwide, the demand for protein products such as meat and eggs is increasing [3,4]. To meet this need, an alternative mechanism is to increase housing and raise more birds. This practice, coupled with labor shortages and increased biosecurity measures, makes it difficult for producers to monitor the production, health and welfare of all their birds [5]. Therefore, to facilitate management and improve production efficiency, poultry production has gradually
shifted from discrete and miniaturized to intensive and large scale in the past few decades. However, in dense environments, the risk of disease transmission would be increased. In order to solve this problem, breeding scientists are committed to cultivating poultry breeds with both high production performance and high disease resistance. However, with the improvement of production performance, some physiological functions such as adaptability and disease resistance of poultry are limited [6]. Vander [7] found that high productivity induced high susceptibility to MD (Marek’s disease) and Lamont [8] found that egg production performance was negatively correlated with resistance to MD.

Poultry disease, regarded as one of the crucial factors affecting poultry production, has restricted the development of the poultry industry for a long period [6]. Although researchers and breeders have conducted a lot of work in disease prevention and control, such as disease-resistant breeding [6,9], immune-related products [10,11] and enhancement of routine measures, the outbreak of poultry diseases is still inevitable, which will not only cause huge economic losses, but some zoonotic infectious diseases may also endanger human life [12–14]. Since the European Union banned the use of antibiotics as growth promoters in 2006 [15], the poultry industry has entered an era without antibiotics, which may lead to adverse effects on production performance (such as weight gain, feed conversion ratio, mortality rate and yield) [16]. In addition, there was another European Union announcement to phase out and eventually prohibit the use of cage-rearing systems to rear laying hens in all European Union member countries by 2027, which will undoubtedly exacerbate the negative impact of disease on poultry industry. Studies have shown that the mortality of laying hens during the laying period is related to the rearing patterns, with the mortality rate in free-range systems nearly twice that of the cage-rearing systems [17,18].

Disease surveillance and early warning are necessary to decrease poultry mortality and increase yields. Traditional disease detection methods rely mainly on experienced veterinarians for manual observation or biochemical testing with related instruments [19]. Biochemical testing is sensitive, and its results usually are reliable, but it usually involves complex sample pretreatment steps and requires professionals to operate, so it is not conducted in real time and usually expensive. Manual inspection is time consuming, labor intensive and may produce inaccurate results. Traditional poultry disease surveillance methods may miss the best time for disease warning, especially for some severe infectious diseases, which can no longer meet the needs of the rapidly developing poultry industry. Sick poultry can be identified from multiple aspects, such as vocalization, body temperature, feces and daily behaviors, which may have corresponding abnormal changes. Therefore, the health state of poultry can be evaluated from these clinical symptoms. Figure 1 shows the route of infection and possible clinical symptoms of poultry diseases.

![Figure 1](image-url)  
**Figure 1.** The route of infection and possible clinical symptoms of poultry diseases. Disease infection in poultry can be divided into endogenous and exogenous infection according to the pathogen source. Poultry diseases may cause clinical physiological and behavioral changes and these diseases may be transmitted horizontally or vertically in the flock.
Some existing reviews have summarized and analyzed the related studies on livestock and poultry welfare indicators monitoring and pathogen diagnosis from the technical perspective [19–24]. This review focuses on the clinical symptoms that can be used for early warning and detection of chicken diseases and tries to expound on these symptoms in detail via two dimensions: (1) early disease detection through physiological characteristics, and (2) early disease detection through behavioral characteristics. To detect these characteristics, some monitoring devices will be used, such as microphones and cameras to determine vocalizations; temperature sensors and infrared thermal imagers to determine birds’ temperature; acceleration sensors and cameras to note birds’ activity; and digital cameras to determine the posture and feces of the birds. Figure 2 shows some commonly used state-of-the-art devices that can be used to detect clinical warnings of poultry diseases.

Figure 2. Some commonly used state-of-the-art devices, including microphones, sensors and cameras, can be used to obtain physiological and behavioral information of poultry to detect clinical warnings of poultry diseases.

The references used in this review were retrieved from the Web of Science databases. A combination of the following terms was used for reference retrieval: “Poultry/Chicken/Laying hens/Broiler”, “Health status”, “Disease”, “Vocalization/Sound/Audio/Acoustic”, “Temperature”, “Feces/Manure/Excrement”, “Behavior/Activity/Posture”, “Warning/Detection/Monitoring/Diagnosis”, “Machine learning”, “Deep learning” and synonyms of the above terms (Supplementary Materials Figure S1). The references were included by the following criteria: (1) The study monitored at least one behavioral or physiological indicator that could be used to reflect chicken health status with a non-invasive intelligent method. (2) The method used in the study is introduced in detail. (3) The study focuses on real-time monitoring on site, and there is no need for human intervention in the monitoring process. This review hopes to achieve the following objectives through detailed analysis of the included references: (1) Provide a basis for the large-scale application of related methods in the future by analyzing the advantages and disadvantages of intelligent monitoring methods. (2) Summarize the clinical symptoms of some common poultry diseases and propose potential clinical symptoms that may be used for disease warning. (3) Put forward the prospect for the future research of poultry disease early warning and detection. In this way, we are looking forward to making a significant contribution to the poultry industry.
2. Early Diseases Detection through Physiological Characteristics

Physiological characteristics of birds contain a wealth of information, which usually can be used to reflect the comfort of the growing environment and the emotional state and health status of animals. In humans, some physiological indicators such as blood biochemical indices [25], blood pressure [26] and body temperature [27] are considered the basis for diseases diagnosis. In poultry, some physiological characteristics including vocalization, feces and body temperature are widely applied in disease detection and early warning as these factors have been confirmed to be associated with disease [28–30]. Consequently, this section focuses on the physiological characteristics that are easy to measure and can truly reflect the health status of poultry.

2.1. Abnormal Vocalization

As an important physiological characteristic, the vocalization of poultry is accepted as an indicator of health and welfare [31,32]. It has been successfully used in the prediction of poultry weight and analysis of pecking activity, which can indirectly reflect the health status of chicken [33–37]. In addition, vocalization is generated by specific organs and is an expression of the physiological signal caused by internal or external factors, which is closely related to the health of the respiratory system. The difference in the vocalization of chickens may be to alert the breeder to pay attention to poor environments or disease infection. Hence, it makes sense to regard vocalization as an early indicator of animals’ health.

Rales, an adventitious sound besides the breathing sound, is one of the common symptoms of respiratory diseases in poultry. Carroll et al. [38] infected six fifteen-day-old chickens with infectious bronchitis virus, and recorded the sound of healthy and infected chickens with a microphone, respectively. In their study, the Mel Frequency Cepstral Coefficients (MFCCs), which is the most widely used feature for speech recognition and can represent the spectrum of animal sounds in a compact form [39], were calculated and input to the C4.5 decision tree to classify the sound of healthy and infected chickens, and the classification accuracy was 73.4%. Decision tree is a kind of sequential model, which has been widely used to build classification models, as such models closely resemble human reasoning and are easy to understand [40]. For the same sound data, Whitaker et al. [41] applied dictionary learning and sparse coding methods to classify sound signals, and the accuracy was improved to 97.85%, and Rizwan et al. [42] developed an extreme learning machine (ELM) and support vector machine (SVM) classifiers to detect rales, and their accuracy was 97.1% and 97.6%, respectively. Banakar et al. [43] have shown that sound signals from poultry infected with different diseases would exhibit different acoustic characteristics that could be distinguished. They divided 308 fourteen-day-old Ross chickens into four groups, with 60 chickens in each group. The first group was considered as the control group (without infection). The second, third and fourth groups were infected with Newcastle disease (ND), infectious bronchitis disease (IBD) and avian influenza (AI), respectively. Figure 3 shows the time domain of the chicken’s sound signals of four classes of healthy, ND, IBD and AI chickens [43]. Then, they combined SVM and Dempster–Shafer evidence theory to identify the four classes of sound data, and an accuracy of 91.15% was finally achieved.

Sound samples and results from the above studies were obtained in a closed environment, which means there is no ambient noises interference, but this is not consistent with the actual situation of commercial farms. Sneezing is a clinical sign of many respiratory diseases. In order to detect sneezing sounds in a situation where multiple noise sources are present, an algorithm was developed and implemented with a sensitivity of 66.7% and an accuracy of 88.4%, which demonstrated the feasibility of an automated sound-based monitoring system for poultry health [44]. Mahdavian et al. [45] extracted five acoustic features (MFCCs, energy of Mel sub-bands, wavelet energy, wavelet entropy and spectral flatness) from healthy and sick chickens for sound classification, and they found that wavelet energy and MFCCs were able to detect Newcastle disease on the fourth day after inoculation with an accuracy of 80% and 78%, respectively. Although the two features
exhibited a similar accuracy, wavelet energy had better performance in detecting healthy chickens while MFCCs were better at detecting challenged birds.

![Figure 3. Sound time domain signals for four classes of chickens: healthy, infected Newcastle disease, bronchitis virus and avian influenza. Reprinted with permission from Ref. [43].](image)

The acoustic features presented by chickens with different diseases usually cannot be described by the same set of features, resulting in the low generalization performance of the model established by artificial feature engineering. Therefore, deep learning models were applied to address this problem, which can extract features from input data automatically and avoid complex feature engineering [46]. In the study carried out by Cuan et al., two deep learning models RNN (Recurrent Neural Network) and CNN (Convolutional Neural Network) models were used to classify the chicken sounds of healthy ones and those infected with (AI) [47]. The results of this study showed that the highest recognition accuracies of CNN were 93.01%, 95.05% and 97.43% on the second, fourth and sixth day after injection with the H9N2 virus, respectively, which were much higher than the recognition accuracies of RNN (49.97%, 55.86% and 57.10%, respectively). This means that the method could deliver warnings to farmers to take necessary measures before an outbreak of AI, which would greatly reduce economic losses. In a recent study, Cuan et al. [48] successfully achieved early warning of ND by analyzing the sound of chickens, and the results showed that the accuracies within the first, second, third and fourth days after infection were 82.15%, 90.00%, 93.60% and 98.50%, respectively, which is important for the improvement of animal welfare and automated monitoring of poultry production.

The cost of identifying animal diseases by sound signals is relatively low, and the application prospect is broad but not yet mature. There are two main difficulties. The first is denoising. In the animal living environment, fan rotation, conveyor belt operation and other activities will produce large environmental noises, which may affect the sound preprocessing and final results. The second is the high sparsity of abnormal sounds. Chicken sound data are continuous, while indicative abnormal sounds usually occupy just a small fraction of a long recording duration in a random way. So, how to design and implement algorithms to improve recognition accuracy and efficiency in the complex environment are problems that must be solved in the future. Furthermore, if the abnormal sound in the chicken house can be spatially located [49], it would further improve the management level of the modern poultry industry and reduce the burden on farmers.

### 2.2. Abnormal Body Temperature

The chicken is a kind of homeothermic animal that produces and dissipates heat to maintain a relatively constant temperature, including core and skin surface temperature [50,51]. However, under pathological or stress conditions, the temperature will change due to infection or emergency response. So, the temperature can be an important physiological indicator for the early warning and detection of chicken diseases.

Footpad dermatitis (FPD) is a condition that causes necrotic lesions on the plantar surface of the footpads in growing broilers, which is considered an animal welfare issue
and could cause huge economic losses [52]. The dielectric constant (DC) value, which can be obtained by measuring the plantar skin of the footpads with a moisture-meter device consisting of an electronic control unit and a sensor probe, is useful in the diagnosis of FPD. Hoffmann et al. [53] found that the DC value would be decreased monotonically with increasing FPD score and the negative correlation between DC and FPD score was significant ($p < 0.0001$). FPD is normally accompanied by a change in the temperature of the plantar surface of the foot and footpads. Plantar temperature measurements were carried out on eighty 10-week-old turkeys by using thermal imaging, and the results showed that footpad temperatures were significantly lower than foot temperatures under normal conditions and the severity of mild footpad dermatitis as scored visually was negatively associated with the temperatures of the plantar surface of the foot and footpads [54]. Furthermore, chickens could be classified into three categories (FPD negative, suspect and positive) according to the temperature change from the metatarsal footpad to the digit extremities [55]. By analyzing the plantar surface temperature of 150 randomly selected hens, it was found that the correlation between samples classified as positive by thermal images and clinical FPD visual score was 86.7%. The result indicates that thermal imaging represents a novel tool for the reliable and noninvasive early detection of foot pathologies, which is a more sensitive indicator of subclinical infection than the visual appraisal. In addition, Liu et al. [56] demonstrated that thermal imaging can obtain the body surface temperature of poultry and identify healthy and sick chickens based on the temperature difference between their heads and legs. The head part of a chicken is a key region for obtaining body temperature information, and its correct identification is crucial. In addition to the algorithm optimization, the installation method of thermal infrared camera is also important. The study of Shen et al. [57] showed that the thermal infrared images collected from 160 cm height and 30° pitch angle are better, and the recognition accuracy of the broiler head is 91.3%.

For AI, researchers have focused on developing portable AI detection devices based on PCR and biosensor technology in recent years [22,58–60]; however, these techniques are relatively expensive and require sophisticated personnel to operate. Consequently, a prototype wearable wireless node with a thermistor and an accelerometer to detect chickens infected with highly pathogenic AI was developed [61]. The results showed that the sudden decrease in body temperature of the infected chickens was detectable before chickens showed clinical signs and gross lesions. There are also studies that applied thermal imaging technology to AI detection. The maximum surface temperature of chickens would increase at least 24 h before the manifestation of clinical signs of AI infection, depending on the severity, which means the surface temperature of chickens could be considered an early indicator of AI [62]. According to the physiological characteristics that the body temperature of dead chickens will decrease, Blas et al. [63] successfully detected dead chickens in poultry production by high-resolution thermal imaging technology, which improved the welfare level of the remaining chickens and reduced the risk of disease transmission.

At present, research related to disease detection based on abnormal body temperature in poultry mostly focuses on leg diseases and avian influenza. Thermal infrared temperature is easily affected by environmental factors and chicken overlap. Thermal infrared temperature is easily affected by environmental factors and chicken overlap. How to obtain high-quality thermal infrared images stably under uncontrollable environmental conditions and how to improve the segmentation accuracy of chicken head and leg areas should receive more attention. In addition, the relationship between poultry body temperature and growth performance and behavior should be paid attention to in the future. In addition, wearable temperature sensors will be more portable and lightweight while pursuing better stability and longer transmission distance.

2.3. Abnormal Feces

Digestive system disease is one of the most widespread diseases in chicken farming, which seriously affects production and animal welfare [64]. When the gastrointestinal tract
of chickens is infected by bacteria or viruses, there will be different degrees of pathological changes according to the severity of infection, which will be manifested as abnormal feces in clinical practice. Figure 4 shows the normal and abnormal feces from typical digestive diseases in chickens.

![Figure 4. The normal and abnormal feces from typical digestive diseases in chickens. The feces of disease-infected chickens may have abnormal changes in color, shape, water content and contents.](image)

Therefore, feces can be used as the basis for the early warning of chicken diseases. Table 1 lists the common diseases causing diarrhea in chickens and the corresponding fecal external characteristics.

Table 1. Common diseases causing diarrhea in chickens and corresponding fecal characteristics.

<table>
<thead>
<tr>
<th>Name of Disease</th>
<th>Vulnerable Time</th>
<th>Degree of Hazard</th>
<th>Characteristics of Feces</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avian influenza</td>
<td>All ages</td>
<td>★★★★</td>
<td>Yellow-brown and watery</td>
</tr>
<tr>
<td>Newcastle disease</td>
<td>All ages</td>
<td>★★★★</td>
<td>Yellow-green and watery</td>
</tr>
<tr>
<td>Infectious bursa disease</td>
<td>3–6 weeks</td>
<td>★★★</td>
<td>Lime watery</td>
</tr>
<tr>
<td>Infectious bronchitis</td>
<td>3–7 weeks</td>
<td>★★★</td>
<td>White and watery</td>
</tr>
<tr>
<td>Avian cholera</td>
<td>Adult</td>
<td>★★★★</td>
<td>Grass-green and watery</td>
</tr>
<tr>
<td>Pullorum disease</td>
<td>0–2 weeks</td>
<td>★★</td>
<td>White mushy</td>
</tr>
<tr>
<td>Coccidiosis</td>
<td>4–6 weeks</td>
<td>★★</td>
<td>Brown-red thin or blood</td>
</tr>
<tr>
<td>Tapeworm disease</td>
<td>All ages</td>
<td>★</td>
<td>Tapeworm eggs</td>
</tr>
</tbody>
</table>

* The degree of hazard was represented by the number of symbol ★: more symbols represent a more hazardous condition.

The traditional method of fecal identification relying on experienced veterinarians is feasible to some extent, but it is time consuming, laborious and prone to misdiagnosis. So, researchers began to use machine learning algorithms to address agricultural tasks.

SVM is a kind of generalized linear classifier that classifies binary data by supervised learning, and its decision boundary is the maximum margin hyperplane for the positive and negative classes [65,66]. Aziz et al. [29] were the first to combine the external characteristics of chicken feces with SVM for chicken disease detection. They used the gray-level co-occurrence matrix, a widely known texture descriptor consisting of the extraction of some statistical measurements about the co-existence of different grey levels from the image [67] to extract 19 texture features of feces, and took the texture feature set as the input of SVM to classify the feces of healthy and diseased chickens. The results showed that the highest
accuracy was 93.75%, which proved the feasibility of detecting sick chickens by feces characteristics, but only 20 samples were used in the experiment, so the results may not be representative. The classification of feces is only the first step, and how to detect abnormal feces in images that contain a lot of feces is crucial. The development of deep learning algorithms makes it possible to deal with larger number of samples. Wang et al. [68] collected 10,000 images of feces of 25- to 35-day-old Ross broilers on commercial chicken farms. They manually marked them into five categories: normal, abnormal shape, abnormal color, abnormal water content, abnormal shape and water content. Their study proposed two object detection models based on CNN to detect and classify feces. The results showed that the Faster R-CNN model had better performance with 99.1% recall and 93.3% average mean precision on the test dataset. This study provides a new idea for the detection of digestive tract diseases in poultry on commercial farms.

The counting and species identification of the parasite in feces are also an important task of the detection of intestinal diseases in poultry. Thanks to the efforts of scholars, this task can be achieved with high accuracy today [69–71]. Although biochemical methods can accurately identify the specific disease, they usually have complex operation processes and are not suitable for the early warning of diseases. On the contrary, it is difficult to diagnose specific disease through the external characteristics of feces, but it has guiding significance for farmers to carry out disease prevention and control measures as soon as possible. In the future, researchers should consider the external characteristics of feces of various diseases in the early, middle and late stages of infection and focus on analyzing the characteristics of feces in the early stages of the disease to achieve the purpose of early warning of disease. In addition, digestive tract diseases can often be diagnosed by certain markers. As a technology that can identify certain substances qualitatively and quantitatively, spectral technology has been used to detect feces on the surface of meat products [72–74]. Still, research on directly applying spectral technology to detect fecal markers has not been reported.

3. Early Disease Detection through Behavioral Characteristics

As one of the most important indicators of animal welfare and health, behavior, which can be reflected by activity and posture, is considered to be the simplest, most commonly used and easiest to understand than stress and production levels [21,75]. Therefore, real-time, automatic and nondestructive monitoring of poultry behavior plays an important role in improving animal welfare and early detection of sick chickens.

3.1. Abnormal Activity

Lameness is a common leg disease in poultry and approximately 30% of the chickens were seriously lame [76]. When poultry activity deviates from normal thresholds, it often indicates the presence of disease. Recent studies have shown that automatic monitoring of flock activity can provide early warning of disease.

Kristensen et al. [77] used cameras to record and describe the undisturbed and abnormal activity levels of broiler chickens at 1, 2 and 3 weeks old, and the results showed that the detection system could notify producers when the activity levels deviated from an expected level at a given age. A gait score is the most commonly used method to detect lameness, which heavily relies on visual observation. To determine automatic monitoring of the activity level of broilers, a new and non-invasive method was developed. Aydin [78] utilized a 3D vision camera with a depth sensor to record the behaviors of broilers, and an image processing algorithm was employed to detect the lying and standing events of broilers and count the number and duration time of lying events. The experiment proved that the classification accuracy of 3D visual camera system was 93% compared with manual marking results, and a method for indirectly evaluating the health status of broilers’ legs was proposed according to the negative correlation between lying duration time and gait score. Later on, Aydin [79] found that speed, step frequency, step length and lateral body oscillation of the broilers were also correlated with gait scores. Furthermore, the amplitude
(difference between highest activity peak and baseline level) was proved to be significantly related to gait score, which will decrease with the declining walking ability [80].

Optical flow analysis, a simple image analysis technique that can calculate the moving velocity of an object on the image plane based on the change in brightness between consecutive images, was used to detect abnormal flock activity at an early stage [81]. Colles et al. [82] used optical flow analysis to detect chickens infected with Campylobacter, and the results showed that Campylobacter-free chicken flocks have higher mean and lower kurtosis of optical flow than Campylobacter-positive ones. The subclinical infection can be identified within the first 7–10 days in this way, which is much earlier than traditional microbiological methods. Flock activity monitoring has also been useful for the early detection of abnormal conditions associated with increased mortality and keel bone fractures in laying hens [83,84]. Furthermore, the flock activity of chickens can be translated into an animal distribution index, which has the potential to indicate some underlying animal health problems [85–87].

The above results suggest that automatic monitoring of poultry activity can detect disease at an early stage. However, most of the current related studies focus on flocks, and how to find the single suspected diseased chicken from the group with abnormal activity will become another breakthrough in improving animal welfare.

### 3.2. Abnormal Posture

Activity is the dynamic characteristics of the chicken, while posture is concerned with the static characteristics. Therefore, it is not difficult to understand that when the body function deviates from homeostasis, the chicken does not often have enough energy to maintain a normal posture.

Zhuang et al. [88] have successfully identified healthy and AI-infected chickens by observing posture changes in broilers. In their study, segmentation algorithms were used to separate the background and chickens first to extract the contour and skeleton information. Then, six eigenvalues (concavity, skeleton attitude angle, shape features, area-linear rate, elongation and circularity) were calculated manually to constitute the eigenvectors, and finally, machine learning algorithms were built to evaluate the health status of broilers, and the results showed that the SVM model had the highest accuracy of 99.469%. The algorithm can automatically detect sick chickens to a certain extent to achieve the purpose of early warning, but the procedures are complicated. Before the health status assessment, the head area of chickens needs to be extracted to determine whether they are in the feeding state. This means the algorithm will not work when the chickens are not completely facing the camera. To analyze the postural differences between healthy and sick chickens infected with Newcastle disease virus, Okinda et al. [89] designed and calculated another set of posture shape features (circle variance, elongation, convexity, complexity and eccentricity), in which walk speed was also included in the eigenvector in their study. The results suggested that early warning can be achieved before a major outbreak occurs. The earliest possible infection detection time was on the fourth day based on circle variance and elongation and the sixth day based on eccentricity and walk speed. Similarly, the SVM model achieved the highest accuracy of 98.8%. Still, the difference is that this method only needs to obtain the top view of the chicken to carry out subsequent recognition, which reduces the dependence on the orientation of the living animal when the image is obtained.

The algorithm based on manual feature extraction can only extract the features that are easy to quantify, such as size, shape, texture, etc., and has a large workload and finds it difficult to achieve model migration for different tasks. Therefore, the poultry posture recognition methods based on deep learning came into being. To automatically detect sick broilers in a flock, Zhuang et al. [90] proposed an optimized model (Improved Feature Fusion Single Shot MultiBox Detector) based on the original Single Shot MultiBox Detector model, which can detect and identify the health status of broilers simultaneously, and achieved 99.7% and 48.1% mean average precision (intersection over union > 0.5, 0.9, respectively). In addition, if the automatic and accurate classification of different
animal postures such as standing, sleeping, food pecking and feather pecking can be achieved, this will provide farmers with better information and further promote efficient flock management [91–93].

4. Conclusions

Disease control is a critical problem for poultry farmers. Traditional manual disease inspection methods cannot meet the needs of the growing number and scale of poultry farms. Clinical symptoms directly manifest from poultry disease. Automatic disease detection and early warning technology based on clinical symptoms have the potential to monitor poultry health status in a real-time, fast and non-destructive way. At present, the detection of poultry diseases is usually based on the sound characteristics, body temperature characteristics, fecal characteristics, production characteristics (water intake, feed intake, etc.), activity characteristics and posture characteristics of the animals. Table 2 lists the comparison of five clinical symptoms used for the early warning of disease.

Table 2. Comparison of five clinical symptoms used for the early warning of disease.

<table>
<thead>
<tr>
<th>Clinical Symptoms</th>
<th>Collection Devices</th>
<th>Monitoring Level</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vocalization</td>
<td>Microphone and camera Group</td>
<td>• Low cost • Easy installation</td>
<td>• High interference from environmental noise</td>
<td></td>
</tr>
<tr>
<td>Temperature</td>
<td>Temperature sensor Individual</td>
<td>• Relatively mature • Widely used • Remote temperature measurement • High visualization degree of temperature distribution</td>
<td>• Insufficient endurance • Short transmission distance</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Infrared thermal imager Group</td>
<td></td>
<td>• Easily affected by the environment</td>
<td></td>
</tr>
<tr>
<td>Feces</td>
<td>Camera Group</td>
<td>• Low cost • Can monitor the chickens in the whole coop</td>
<td>• A bad environment may result in poor equipment life • Strict light conditions are required • No relevant studies have been found</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Spectroscope Group</td>
<td>• Can identify specific biomarkers</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Activity</td>
<td>Acceleration sensor Individual</td>
<td>• Low cost • High sensitivity • Can monitor multiple objects simultaneously</td>
<td>• Easy to fall off • Severely affected by light conditions</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Camera Group</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Posture</td>
<td>Camera Individual</td>
<td>• Little effect on chicken • High intelligence</td>
<td>• Algorithms for solving the chicken overlap problem are not well developed</td>
<td></td>
</tr>
</tbody>
</table>

The above characteristics are mainly collected by machine vision systems, sound pick-up equipment, wearable sensors and other methods, which have advantages and disadvantages. The machine vision method has been relatively mature from the construction of the system to the deployment of the algorithm, but it has the problems of easily limited vision and difficult individual tracking. Sound processing technology has broad application prospects. The price of related equipment is low, but the sound recognition results are susceptible to environmental noise, which means that sound analysis technology may be more suitable for use at night. The wearable sensor is easy to install, and the obtained data are highly reliable, but it may cause stress on poultry, and the signal transmission distance and endurance of the sensor need to be optimized.

Although the importance of clinical symptoms in the early warning of poultry diseases has been recognized, it has not been fully utilized. Cockscomb abnormalities (abnormal color, swollen, scabby, shrunken), ocular anomalies (congestion, lacrimation) and changes in the feathers (fluffy, matte, fall off) of chickens are also important clinical symptoms. Furthermore, Table 3 summarizes the clinical symptoms of common chicken diseases. We hope that these symptoms in column 4 of Table 3 can be used as indicators for the early warning of poultry diseases in future studies.
Table 3. The clinical signs/symptoms and corresponding management measures of common chicken diseases [94,95]. These clinical signs/symptoms could be used as monitoring indexes of disease early warning.

<table>
<thead>
<tr>
<th>Diseases</th>
<th>Causative Agent</th>
<th>Severity</th>
<th>Signs/Symptoms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Newcastle disease</td>
<td>Family: Panornavirusidae Genus: Panamixivirus</td>
<td>Mortality can be up to 100%</td>
<td>Respiratory signs: Gasping and coughing, copious mucoid discharge, edema of tissue around eyes, throat and face, cyanosis of comb and wattles. Nervous signs: Convulsions, torticollis, opisthotonus, drooping of wings, paralysis of legs and wings, enteric signs and greenish diarrhea are frequently seen.</td>
</tr>
<tr>
<td>Avian influenza</td>
<td>Orthomyxoviridae (Virus family)</td>
<td>Mortality can be up to 60%</td>
<td>Pronounced depression and ↓ feed consumption, huddling and ruffled feathers, mild to severe respiratory signs: coughing, sneezing, rales and excessive lacrimation, subcutaneous edema of head and face which may extend to neck and breast, cyanosis of wattles, comb and unfathered skin, areas of diffuse hemorrhage on shanks, nervous disorders, i.e., convulsions, ataxia, mucoid diarrhea (white).</td>
</tr>
<tr>
<td>Infectious bursal disease</td>
<td>Family: Birnaviridae Genus: Birnavirus</td>
<td>Mortality rate 1–50%</td>
<td>Sudden onset and short duration, the tendency for some birds to pick at their own vents, whitish, watery mucoid diarrhea followed by dehydration, soiled vent feathers, anemia, severe depression and ruffled feathers, trembling, incoordination, prostration and finally death.</td>
</tr>
<tr>
<td>Marek’s disease</td>
<td>Marek’s disease virus</td>
<td>Mortality can be up to 100%</td>
<td>Asymmetric progressive paresis. Later complete paralysis of one or more of the extremities. Signs vary from bird to bird as anyone or several nerves may be affected by incoordination and lameness. Bird stretches one leg forward and other backward as a result of paralysis of the leg. Drooping of the limb in case of wing involvement. Dilation of crop and gasping if vagal paralysis. If nerves controlling neck muscles are affected, the head may be held low.</td>
</tr>
<tr>
<td>Fowl pox</td>
<td>Foel pox virus Family: (Poxviridae) Genus (Avipox)</td>
<td>Mortality rate is 1–5%</td>
<td>Cutaneous form (Dry Pox): Mild forms may remain unnoticed, generalized lesions on wattle, comb and unfathered parts of the skin. Diphtheritic form (Wet Pox): White or opaque eruptions in the mouth, nares, pharynx, esophagus, larynx and trachea, caseous white patches coalesce and expand rapidly and become ulcerated. Mucous membranes undergo an extensive fibrin-necrotic process and develop diphtheritic membrane. Dyspnea, gasping and suffocation due to caseous material in the larynx. Death occurs due to suffocation.</td>
</tr>
<tr>
<td>Coccidiosis</td>
<td>Eimeria acervulina, Eimeria necatrix, Eimeria tenella, Eimeria Mitis, Eimeria Tenella, Eimeria maxima and Eimeria brunetti.</td>
<td>Mortality can be up to 50%</td>
<td>Coccidiosis can be divided into 2 groups: Cecal coccidiosis: Mainly caused by E. tenella in chickens up to 12 weeks old. Mortality may run as high as 50%. Infected birds are listless, have bloody dropplings and a pale comb and show a lack of appetite. Laboratory examination will show hemorrhages in the cecal wall. After severe bleeding, a core will be formed in the lumen. Small intestinal coccidiosis: Caused by E. acervulina, E. brunetti, E. maxima, E. necratris, E. tenella and E. mitis. May affect birds of any age. E. acervulina is not normally very pathogenic, but in some cases, considerable mortality may be seen. Birds infected show loss of weight, combs may be shriveled and a drop or even cessation of egg production in layers may be seen.</td>
</tr>
<tr>
<td>Pullorum disease</td>
<td>Salmonella pullorum Family: Enterobacteriaceae</td>
<td>Mortality can be up to 100%</td>
<td>The incubation period is 4–5 days. Large numbers of dead in-shell chicks or chicks die shortly after hatching. Loss of appetite and huddling together. Sagging of wings and distorted body appearance, pot-bellied, chalky white excreta (white diarrhea), vent pasting, labored breathing or gasping.</td>
</tr>
</tbody>
</table>

The transformation of the poultry industry to information and intelligence is the trend of future development. The development and application of disease early warning technology can effectively liberate the labor force and improve animal welfare and farm management level. In particular, early warning of infectious diseases can avoid the outbreak of diseases in chickens to a certain extent, greatly reduce the economic losses caused by diseases and increase the comprehensive economic benefits. The traditional breeding pattern inevitably requires a large number of people to participate, and more people represent more potential pathogens, which is extremely unfavorable for intensive farming systems. Therefore, another important advantage of farms empowered by intelligent technology is to minimize the flow of farm personnel, which can significantly improve...
biological safety. In the end, the development trends of intelligent automatic monitoring technology for poultry diseases based on clinical symptoms are prospected: (1) Establish the database of poultry characteristics, including different regions, chicken species, disease categories and clinical data. (2) Accelerate the optimization of disease detection algorithms to improve the accuracy and at the same time limit the size of the model to reduce the computational burden for algorithm deployment. (3) Integrate a variety of clinical characteristics to comprehensively evaluate the health status of poultry, and finally establish an expert system for the early warning of poultry diseases. (4) Develop and design complete sets of intelligent equipment for poultry disease detection and early warning.

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**Supplementary Materials:** The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/app12115601/s1, Figure S1: PRISMA flowchart.

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