Ann. Anim. Sci., Vol. 25, No. 1 (2025) 23–33 *DOI: 10.2478/aoas-2024-0039*

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USING ARTIFICIAL INTELLIGENCE TO IMPROVE POULTRY PRODUCTIVITY – A REVIEW

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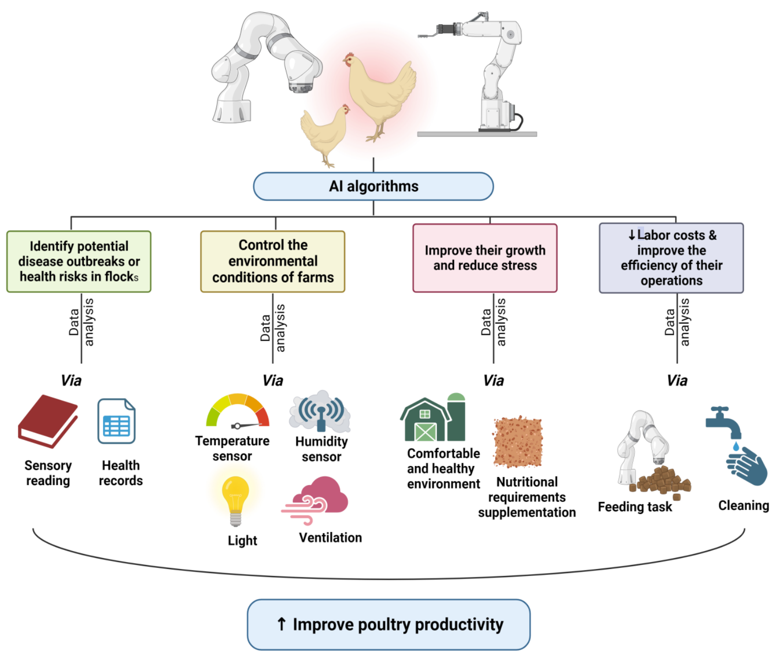
Abstract

A recent study investigated the potential applications of artificial intelligence (AI) in poultry farming. One area where AI can be helpful is in the early detection of diseases. By analyzing data from various sources, such as sensor readings and health records, AI algorithms can identify potential disease outbreaks or health risks in flocks, allowing farmers to take timely preventive measures. Another area where AI can be applied is in controlling the environmental conditions of farms. By analyzing data from sensors that monitor temperature, humidity, ventilation, and lighting conditions, AI algorithms can help farmers create a comfortable and healthy environment for birds, improving their growth and reducing their stress. AI can also optimize the management of healthcare supplies for poultry. By analyzing the nutritional requirements of birds and the availability and prices of different ingredients, AI algorithms can help farmers optimize feed formulations, reducing waste and environmental impacts. Finally, the study explored the use of robots in poultry care. Robots can be used for cleaning, feeding, and monitoring individual birds. By automating these tasks, farmers can reduce labor costs and improve the efficiency of their operations. Overall, the study highlights the potential benefits of using AI and robotics in poultry farming, including early disease detection, improved environmental conditions, optimized feed formulations, and increased automation.

Key words: artificial intelligence, robotics, disease detection, environmental monitoring

Graphical abstract



The poultry industry faces various challenges, such as labor shortages, disease outbreaks, and animal welfare issues that can negatively impact productivity and profitability (Caldwell, 2012; Hafez et al., 2020). Technology solutions, such as artificial intelligence (AI), have been proposed to address these challenges and accommodate the increasing demand for poultry meat (Corkery et al., 2013; Mortensen et al., 2016). Animal welfare and care are critical components of sustainable animal husbandry, but traditional methods may fall short in addressing various conditions of health, safety, behavior, and stress levels (Mitchell and Kettlewell, 2009). Fortunately, AI technologies are expected to improve animal welfare and productivity, leading to a possible future where autonomous systems optimize every aspect of chicken farming and processing (Vroegindeweij et al., 2018; Patel et al., 2022).

AI has been the subject of research on non-structured (such as image, video, and voice) and structured (such as textual) data collection, analysis, processing, recognition, and modeling that can relate to animal behavior, welfare, diseases, and environmental management (Ren et al., 2020). For example, visual images (Manjeet et al., 2019), video (Küçüktopcu and Cemek, 2021 a), and audio (Bao et al., 2022) data can be used for animal location tracking (Barros et al., 2020) and behavior recognition (Jin et al., 2021).

In poultry farming, early detection of illnesses and prompt intervention can help prevent disease outbreaks and improve food safety (Ren et al., 2020). Monitoring body comfort, stress levels, and air quality parameters such as carbon dioxide and ammonia levels can also improve animal welfare. Therefore, implementing AI and Internet of Things-based systems can help manage and monitor chicken farms more efficiently (Ren et al., 2020).

The next parts depict the chicken farm of the future and explain how intelligent automation will make it possible.

Environmental requirements

Environmental requirements are critical to ensure poultry's health, welfare, and productivity (Mijwil et al., 2023). These requirements include temperature, humidity, lighting, ventilation, and air quality. No change is needed, but consistency is ensured in discussing the specific AI applications managing each environmental parameter mentioned (Sadeghi et al., 2015).

Temperature and humidity levels should be carefully controlled and monitored, with appropriate adjustments made based on the age and type of bird. Lighting conditions should be optimized to provide the appropriate photoperiod for different stages of production. At the same time, ventilation systems must be appropriately designed and maintained to provide adequate air exchange and prevent the buildup of harmful gases. Air quality is also crucial, as poor ventilation can lead to high ammonia and other harmful gases, negatively impacting the birds' respiratory health.

Artificial intelligence can be crucial in managing these environmental requirements by monitoring and analyzing data from sensors and other sources (Barsagadea and Rumaleb, 2024). For example, AI algorithms can predict temperature and humidity trends, identify areas of poor ventilation, and monitor air quality levels. This information can then be used to adjust to environmental conditions and prevent health issues before they arise. AI can also help optimize production efficiency by providing insights into feed consumption, growth, and mortality rates.

The heat

Infrared thermal imaging technology has proven to be effective in controlling the ambient temperature in poultry farms while also ensuring the welfare of the birds (Depuru et al., 2024). Heat stress is a critical issue that can negatively impact poultry health and immunity, potentially leading to significant mortality rates. Infrared thermal imaging (IRTI) technology can be a non-invasive method to measure the surface body temperature and identify the onset of fever, an early sign of disease (Ben Sassi et al., 2016). The technology can also represent different body temperatures in distinct hues, making monitoring the birds' temperature changes easier. Additionally, the facial surface temperature can measure degrees of thermal stress and provide more information about the birds' condition than the ambient temperature (Astill et al., 2020). These technological advancements have significant implications for improving poultry farms' welfare and productivity (Figure 1).

The humidity

Humidity is an essential environmental factor in poultry farming as it can significantly impact bird health and performance. High humidity levels can contribute to the growth of harmful microorganisms, such as bacteria and fungi, which can lead to respiratory and other health problems in poultry (Wang et al., 2023). On the other hand, low humidity levels can cause dehydration and stress, leading to reduced growth and egg production (Mavani et al., 2022). Maintaining optimal humidity levels in poultry houses is essential for ensuring bird health and productivity.

One method for controlling humidity levels in poultry houses is through ventilation systems. Proper ventilation can help remove excess moisture from the air, reducing humidity levels and preventing the growth of harmful microorganisms. Additionally, using absorbent materials, such as litter and bedding, can help control humidity levels by absorbing excess moisture from the environment (Mavani et al., 2022).

In recent years, there has been growing interest in using artificial intelligence (AI) to optimize environmental conditions, including humidity levels, in poultry houses. AI can analyze temperature, humidity, and other environmental factors data to identify patterns and make real-time adjustments to ventilation systems and other controls (Kumar et al., 2021). This can help ensure optimal humidity levels and improve bird health and productivity. Overall, controlling humidity levels in poultry houses ensures bird health and productivity. Using ventilation systems and absorbent materials can help maintain optimal humidity levels, while AI technology can help optimize environmental conditions in real time (Figure 2).

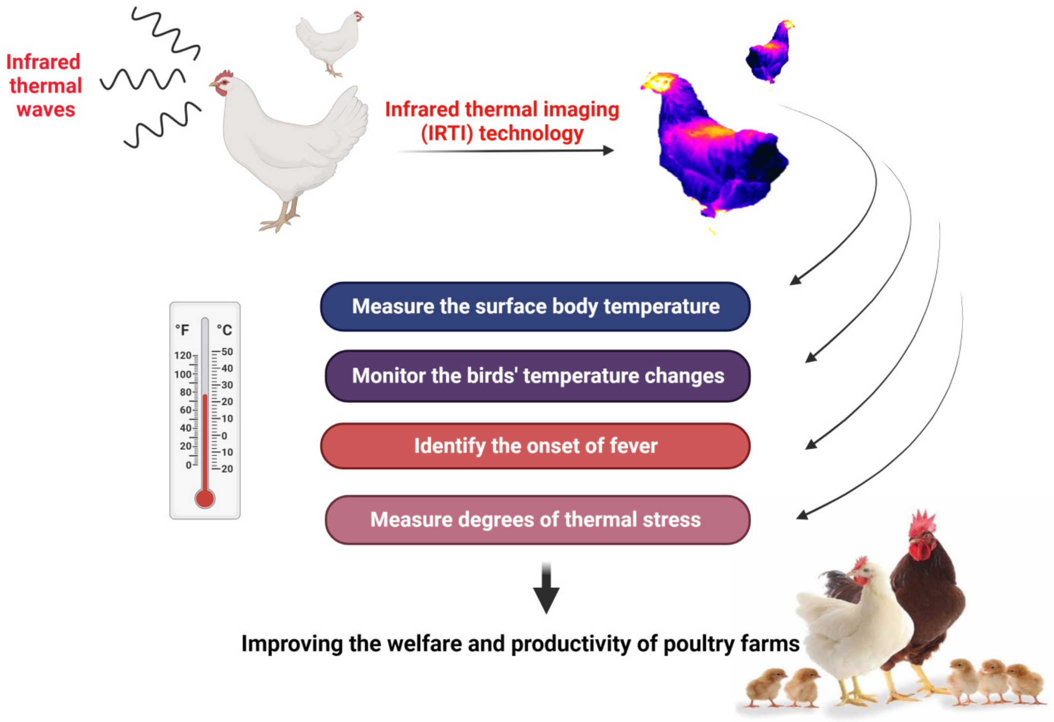


Figure 1. The importance of using AI such as infrared thermal imaging (IRTI) technology to improve the welfare and productivity of poultry farms

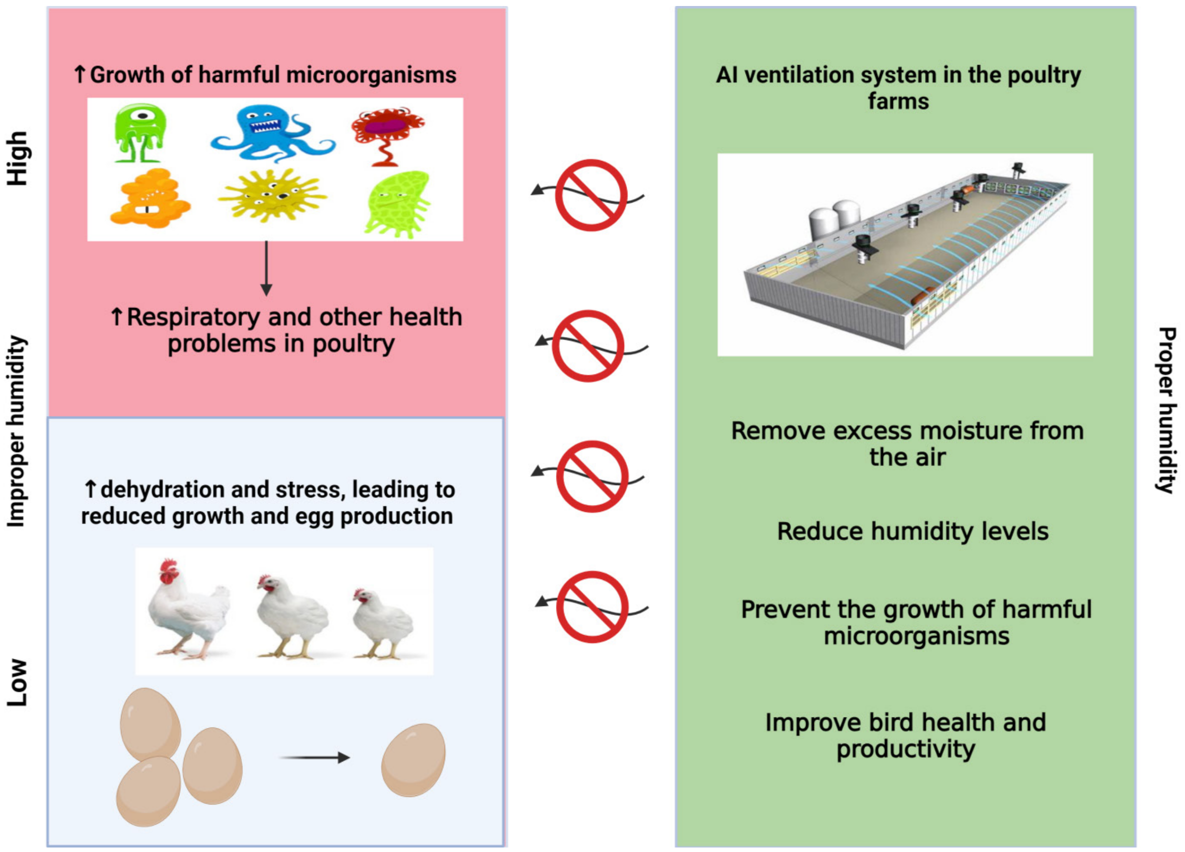


Figure 2. Using AI ventilation system in poultry houses

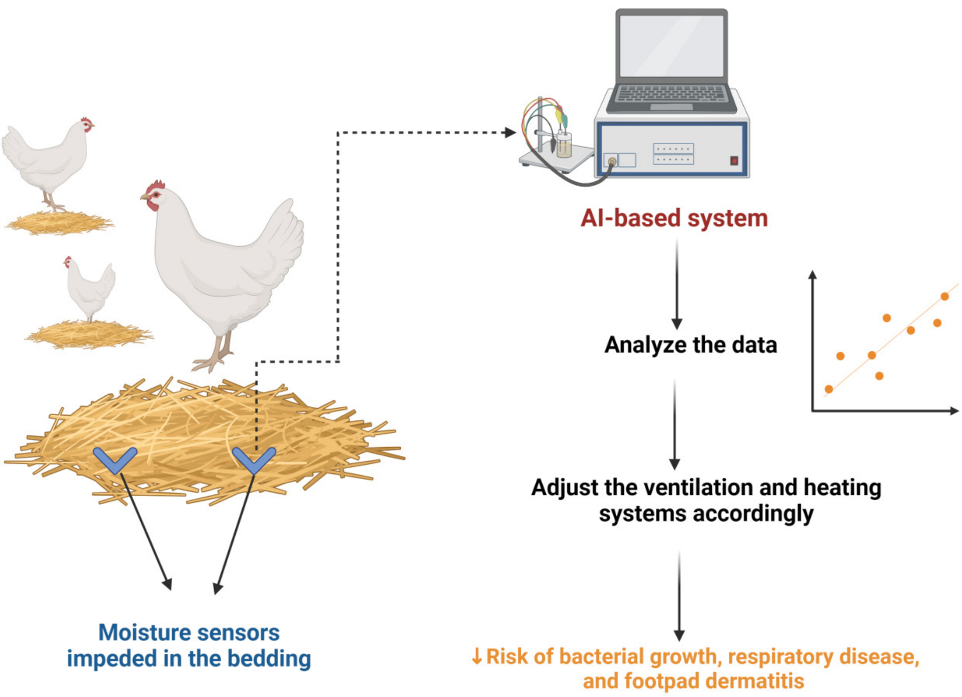


Figure 3. The AI-based system controls mattress moisture

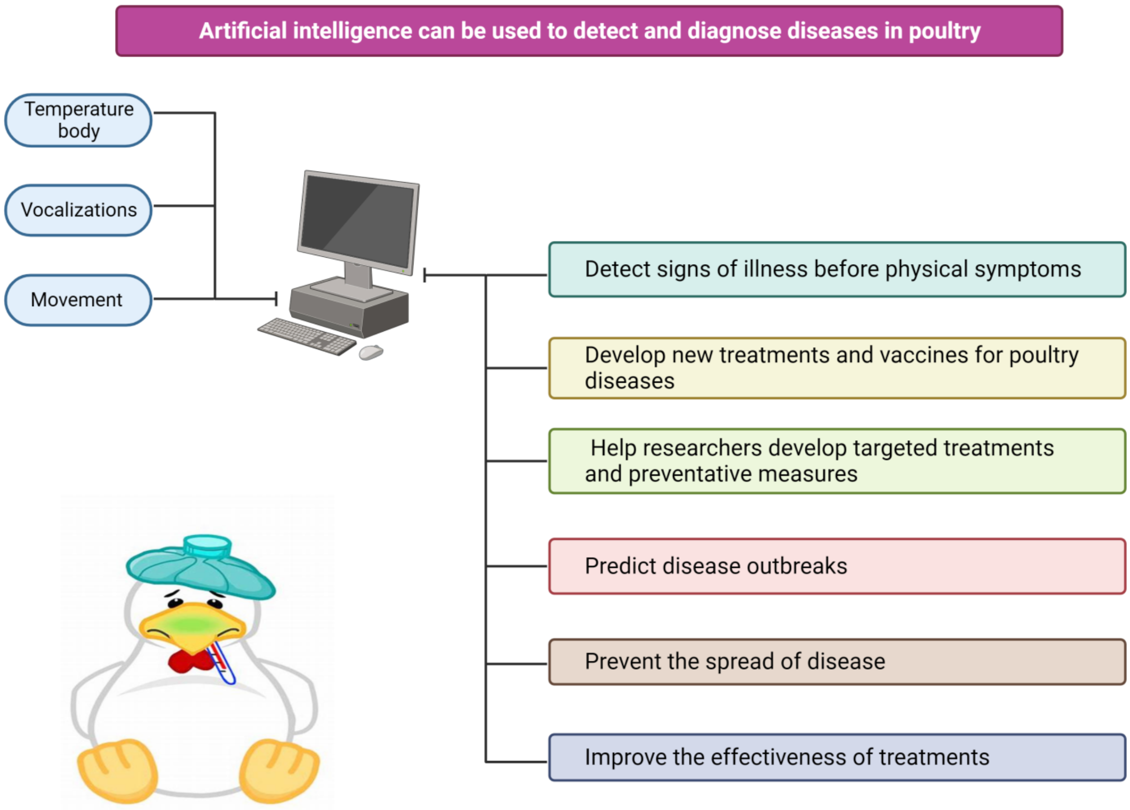


Figure 4. Artificial intelligence can be used to detect and diagnose diseases in poultry

The aeration

Proper ventilation is essential for maintaining optimal air quality and reducing the risk of respiratory diseases in poultry farming. Artificial intelligence can help monitor and control ventilation systems, ensuring they function effectively. Sensors can measure air quality, temperature, humidity, and carbon dioxide levels. AI algorithms can then analyze the data collected from these sensors to determine the optimal settings for the ventilation system. This can improve air quality, reduce energy consumption, and increase productivity (Garcia and Caldara, 2014).

Research has shown that AI-based ventilation control can reduce ammonia and carbon dioxide levels in poultry houses and improve bird health and welfare (Zhuang et al., 2018). In addition, AI can detect and alert farmers to ventilation system malfunctions or failures, allowing for prompt repair and maintenance. This can prevent the buildup of harmful gases and improve overall farm safety. Using AI in poultry farming can improve ventilation management, resulting in better air quality, animal health and welfare, and farm productivity (Zhuang et al., 2018).

Mattress moisture

Controlling mattress moisture is crucial for maintaining the health and welfare of poultry. Moisture in the bedding material can lead to an increased risk of bacterial growth, respiratory disease, and footpad dermatitis (Rico-Contreras et al., 2017). Artificial intelligence can help monitor and manage the moisture levels in the bedding material. One way to monitor moisture levels is by using sensors embedded in the bedding material. These sensors can collect data on moisture levels and send it to an AI system that can analyze the data and adjust the ventilation and heating systems accordingly. Additionally, environmental sensors are primarily used to monitor environmental conditions, i.e., temperature, humidity, and air quality, to provide the appropriate conditions suitable for the significant efficiency of animal production. Importantly, inadequate temperature, relative humidity, and exposure length substantially impact broiler welfare, mortality, and performance (Debauche et al., 2020). Furthermore, exposure to elevated levels of noxious gases like carbon dioxide and ammonia can reduce weight, feed conversion, overall viability, and loss of profit in the poultry industry (Küçüktopcu and Cemek, 2021 b) (Figure 3).

Another approach is to use machine learning algorithms to analyze data on the behavior of the poultry concerning the moisture levels in the bedding material. For example, a study by Rico-Contreras et al. (2017) used machine learning algorithms to predict broiler behavior based on environmental data, including moisture levels in the bedding material.

Age determination of poultry

Age determination of poultry is a critical task in animal husbandry as it allows farmers to make informed decisions about feeding, vaccinations, and culling. Traditional age determination methods, such as visual inspection and weighing, can be time-consuming and inaccurate. Artificial intelligence (AI) can provide a more efficient and accurate solution to this problem. Machine learning algorithms have been trained on various data sources, such as images of birds, their vocalizations, and their movements, to predict their age accurately. For example, one study used deep learning algorithms on images of broiler chickens to predict their age (Guo et al., 2022). AI-based age determination has the potential to revolutionize the poultry industry by providing farmers with accurate and timely information about the age of their birds. This can lead to better management practices, improved animal welfare, and increased productivity (Guo et al., 2022).

Diseases

Artificial intelligence can be used to detect and diagnose diseases in poultry. By analyzing data from various sources, such as body temperature, movement, and vocalizations, AI algorithms can detect signs of illness before physical symptoms are visible to human caretakers. This early detection can help prevent the spread of disease and improve the effectiveness of treatments (Kumar et al., 2022). Additionally, AI can predict disease outbreaks by analyzing weather patterns, flock demographics, and other factors that may contribute to the spread of disease. By identifying risk factors and taking preventative measures, farmers can reduce the likelihood of disease outbreaks and minimize their impact when they do occur (Mbelwa et al., 2021).

Finally, AI can be used to develop new treatments and vaccines for poultry diseases. By analyzing genetic data and identifying patterns in disease progression, AI algorithms can help researchers develop targeted treatments and preventative measures that are more effective than traditional methods (Walsh et al., 2019) (Figure 4). Ojo et al. (2022) article provides a comprehensive review of the use of AI-enabled Internet of Things (IoT) applications in managing poultry health and welfare. The focus is on poultry welfare, as the poultry industry faces challenges in assessing welfare parameters and implementing robust monitoring systems, particularly for broilers' health and disease prevention. The review highlights the potential of modern digital technologies in automating poultry management operations, leading to cost-effective and high-quality production. The study systematically examines the current state-of-the-art AI-enabled IoT systems and their recent advancements in the poultry industry. It also outlines the key applications of digital technologies in managing poultry welfare. Lastly, the article discusses the challenges and opportunities of AI and IoT in poultry farming.

Identify diseases

Different AI-based methods for the identification of various diseases and behaviors of birds are briefed in Table 1.

The pictures

Artificial intelligence can be used to identify diseases in poultry through pictures or images. This technique is computer vision and involves training a machine-learning model to recognize patterns in images of poultry affected by various diseases. For example, early detection of poultry diseases is crucial for preventing large-scale outbreaks and minimizing economic losses. This study focuses on real-time monitoring of poultry health status using digital image processing and machine learning algorithms. Healthy broilers were compared with broilers infected with the bird flu virus through manual inoculation. Images of the broilers were obtained, and segmentation algorithms were developed to extract their outlines and skeleton information (Machuve et al., 2022).

Posture features were then extracted using a preset algorithm, and machine learning algorithms were employed to analyze and predict the health status of the broilers. Experimental results demonstrated high accuracy rates, with the Support Vector Machine (SVM) model outperforming other algorithms with a 99.469% accuracy rate on test samples. The proposed algorithms effectively separated broilers from the background, extracted posture information, and accurately identified the health status of broilers. The digital image processes and machine learning techniques showed high accuracy, stability, and generalization performance, providing early warning signals for broiler health status. This research is a reference for future intelligent identification of broiler health status (Zhuang et al., 2018).

Similarly, another study used machine learning algorithms to analyze images of chickens affected by Marek's disease, a viral disease that causes tumors in poultry. The model could accurately identify infected birds with an accuracy rate of over 90% (Quach et al., 2020).

These studies demonstrate artificial intelligence's potential in identifying poultry diseases through images, which can help farmers and veterinarians quickly and accurately diagnose and treat diseases in flocks. Those deep learning techniques, specifically a deep Convolutional Neural Network (CNN) model, can detect common poultry diseases such as coccidiosis, salmonella, and Newcastle early. These diseases often go undetected due to limited access to agricultural support services. The study collected 1,255 laboratory-labeled fecal images and 6,812 farm-labeled fecal images and used several different CNN models to classify healthy and unhealthy fecal images. Fine-tuning the models improved accuracy, with the MobileNetV2 model ultimately recommended for deployment due to its lighter weight and better generalization ability (Machuve et al., 2022).

The video

Timely detection of poultry diseases is crucial for various reasons, including economic impact, animal welfare, food safety, and prevention of zoonotic infections. This study introduces a machine vision-based monitoring system for broiler chickens moving through a designated area (Neethirajan, 2022). Two groups of broilers were observed: a control group and a treatment group inoculated with virulent Newcastle disease virus. The broilers were monitored using video surveillance for data labeling and a depth camera for automated health status classification. Feature variables were extracted based on 2D posture shape descriptors (circle variance, elongation, convexity, complexity, and eccentricity) and mobility features (walk speed). Statistical analysis revealed that all investigated features were statistically significant ($P<0.05$) in the treatment group over time after the challenge. Circle variance and elongation showed the earliest possible detection of infection on the 4th day, while eccentricity and walk speed provided detection on the 6th day. However, convexity and complexity did not contribute to early detection. Two classifiers were developed based on combined posture shape descriptors and all feature variables. The Support Vector Machine (RBF-SVM) model outperformed others, achieving accuracies of 0.975 and 0.978, respectively. The proposed automatic broiler monitoring system provides continuous and non-intrusive early warning and predicts disease occurrence (Okinda et al., 2019).

A study proposes a deep learning model based on You Only Look Once (YOLOv5) for automatically detecting, counting, and tracking individual and grouped chickens in the poultry industry. The model addresses challenges such as complex backgrounds, varying lighting conditions, and occlusions from feeding and water stations. It incorporates a multiscale feature and mapping modules to improve tracking precision. The model was trained and tested on a dataset, demonstrating enhanced tracking accuracy. It utilizes the Kalman Filter to track multiple chickens simultaneously, associating individuals across video frames for real-time and online applications. The proposed model excels in detecting chickens amidst background interference, accurately counting them, tracking their movement and measuring their path and direction. This enables continuous monitoring of chicken behavior on-farm, including perching, walking, social interaction, and environmental exploration, providing valuable insights into their natural behaviors. The study emphasizes the potential of the ChickTrack model as a digital tool to promote science-based animal husbandry practices and improve the welfare of chickens in farming (Neethirajan, 2022). Using artificial intelligence and computer vision techniques to identify poultry diseases through video is possible. One approach is to use deep learning models, such as convolutional neural networks (CNNs), to classify poultry diseases based on visual symptoms.

A large dataset of labeled videos of healthy and diseased poultry is needed to develop such a system. The videos can be captured using cameras installed in poultry farms or during veterinary inspections. The videos should capture different angles and lighting conditions to increase the diversity of the dataset. Once the dataset is collected, it can train and validate a CNN model. The model should be designed to extract relevant features from the video frames and classify them into different disease categories. Transfer learning can be used to leverage pre-trained CNN models, such as VGG, ResNet, or Inception, to improve the performance of the disease classification model (Neethirajan, 2022). The system can be deployed as a web or mobile application, allowing farmers or veterinarians to upload poultry videos for disease diagnosis. Then, it processes the video and provides the user with a diagnosis and treatment recommendations. Identifying poultry diseases through video using artificial intelligence has become an increasingly popular research topic in recent years. AI has the potential to provide an efficient and accurate method for detecting diseases in poultry flocks, which can help to prevent economic losses and improve animal welfare (Neethirajan, 2022).

The sound

Sex detection method for chicks is based on their calls, which is important for efficient poultry breeding. Deep learning techniques are employed to classify chick calls and determine their sex. The study examines three chick varieties and compares three audio features: Spectrogram, Cepstrogram, and MFCC+Logfbank. These features are input for five types of neural networks: CNN, GRU, CRNN, TwoStream, and ResNet-50. Through cross-comparison experiments, the ResNet-50 network trained with MFCC+Logfbank audio features achieves the % test accuracy of 83% for three-yellow chicks' calls. The GRU network trained with Spectrogram audio features obtains the highest accuracy of 76.8% for native chicks' calls. In comparison, the ResNet-50 network trained with Spectrogram audio features achieves the highest accuracy of 66.56% for flaxen-yellow chicks' calls (Mbelwa et al., 2021).

Multiple calls from each chick are detected, and the majority voting method is used for sex determination. When detecting the sex of three yellow chicks, the ResNet-50 network achieves a sex detection accuracy of 95%. For native chicks, the GRU network uses Spectrogram and spectrogram features and the CRNN network uses Spectrogram features to achieve a sex detection accuracy of 90%. When detecting the sex of flaxen-yellow chicks, the Twostream network trained with MFCC+Logfbank features and the ResNet-50 network trained with Spectrogram features achieved an accuracy of 80%. The results highlight significant sex differences among chick calls across different breeds. The method demonstrates better applicability for three-yellow chicks than native and flaxen-yellow chicks. Moreover, the accuracy decreases when detecting the sex of chicks from breeds not included in the training data (Li et al., 2022).

Sadeghi et al. (2015) implemented an intelligent method for detecting and classifying chickens infected with *Clostridium perfringens* type A based on vocalization. Two groups of chickens were divided into separate cages. On day 14, they were inoculated with *Clostridium perfringens* type A. Vaccines were administered to prevent secondary diseases from influencing the vocalization patterns. Chicken vocalization was recorded daily for 30 days under controlled conditions, and 23 features were extracted from the sound signals. Fisher Discriminate Analysis (FDA) was used to select the five most important features. A Neural Network Pattern Recognition (NNPR) structure with one hidden layer was trained to detect and classify healthy and unhealthy chickens. The neural network achieved classification accuracies of 66.6% on day 16 and 100% on day 22, demonstrating its effectiveness in diagnosing diseases in chickens.

In the study by Jung et al. (2021), cattle and laying hens were captured on audio and video. They divided the sounds of cattle into nine classifications and the sounds of laying hens into eight classes. Creating convolutional neural network (CNN) models utilizes classified audio recordings. Two CNN structures – one based on a 2D ConVnet and the other on a 1D model with long short-term memory – were constructed and evaluated to classify the vocalizations of laying hens and cattle. Another study proposes a deep learning solution using Convolution Neural Networks (CNN) to predict the classification of chicken feces. The XceptionNet model outperforms other models in all metrics, with a validation accuracy of 94% using pretraining. The fully trained CNN comes second, but the pre-trained XceptionNet method has the highest prediction accuracy (Mbelwa et al., 2021).

Cuan et al. (2022) introduced the deep poultry vocalization network (DPVN) for early detection of Newcastle disease (ND) using poultry vocalization. The method uses multiwindow spectral subtraction and high pass filtering to reduce noise. The method achieved high accuracy, recall, and F1-score of 98.50%, 96.60%, and 97.33%, respectively, with accuracies within the first, second, third, and fourth days after infection. Overall, these studies demonstrate the potential of AI-based approaches for identifying and diagnosing poultry diseases through sound analysis, which could help farmers and veterinarians detect and treat diseases more quickly and effectively (Mbelwa et al., 2021).

The movement and shape of birds

Identifying poultry diseases through the movement and shape of birds with the help of artificial intelligence has been a topic of recent research. Several studies have investigated the potential of using computer vision and machine learning techniques to detect and classify bird movements and postures associated with various diseases. For example, Xie and Chang's (2022) study introduces a scheme for identifying broiler behavior using object detection and recurrent-based artificial neural networks. The proposed approach involves utilizing a trained YOLOv4 object detection model to identify specific parts of the broiler chicken, constructing a chicken skeleton based on these parts, and extracting the angle between the backbone fulcrum vectors. Subsequently, broiler behaviors are detected through a time-series-based long short-term memory (LSTM) network.

The scheme was validated outdoors, achieving an average precision, average recall, and F1-score of 82%, 81%, and 81%, respectively. Additionally, the paper discusses and analyzes the performance comparison using a multilayer perceptron (MLP) network in conjunction with the YOLOv4 model. Overall, these studies demonstrate the potential of using artificial intelligence and computer vision techniques to identify poultry diseases through the movement and shape of birds. By automating the detection process, these techniques can help improve the efficiency and accuracy of disease diagnosis and ultimately contribute to poultry populations' overall health and well-being (Cuan et al., 2022).

The use of sensors in artificial intelligence

Sensors play a crucial role in artificial intelligence by providing data to the algorithms that power AI systems. Sensors can capture data from the physical world, such as temperature, pressure, motion, and light, and convert that data into digital signals that AI algorithms can analyze.

This data can be used to train machine learning models, make predictions, and control actions in real time. Many types of sensors are used in AI, including cameras, microphones, accelerometers, gyroscopes, temperature sensors, pressure sensors, and more. These sensors can be integrated into smartphones, wearable, drones, and smart home systems, allowing AI algorithms to analyze the data and make decisions based on that information. One example of the use of sensors in AI is in autonomous vehicles. Sensors such as lidar, radar, and cameras gather data about the vehicle's surroundings, including other vehicles, pedestrians, and road conditions. This data is processed by AI algorithms to control the vehicle's speed, direction, and other actions, allowing it to navigate on its own safely (Mbelwa et al., 2021).

Another example is the healthcare industry, where sensors can monitor patients' vital signs and alert healthcare providers to potential issues. Wearable sensors can track a patient's heart rate, blood pressure, and other metrics, and AI algorithms can analyze the data to identify patterns and predict potential health problems. Overall, sensors are a critical component of artificial intelligence, enabling AI systems to collect and analyze data from the physical world and make decisions based on that information. Sensors have become increasingly popular in identifying poultry diseases through artificial intelligence. Sensors such as cameras, accelerometers, and GPS devices can collect data on bird movement, activity, and location, which AI algorithms can then analyze to detect signs of illness or distress (Mbelwa et al., 2021).

Bao et al. (2021) addressed the issue of manual inspection to identify dead and sick chickens in farms by proposing a sensor detection method based on artificial intelligence. The method involves measuring the maximum displacement of chicken activity using foot rings and calculating the three-dimensional total variance representing activity intensity. A detection terminal collects the sensing data from the foot rings through a ZigBee network. Machine learning algorithms are then employed to identify the state of the chickens (dead or sick). This method's combination of artificial intelligence and sensor networks achieves a high recognition rate while reducing operational costs. Practical results demonstrate a 95.6% accuracy in identifying dead and sick chickens, with a 25% cost reduction compared to manual operations over four years.

Other studies have explored using sensors in combination with other techniques, such as thermal imaging, to identify specific diseases. For example, one study used thermal imaging and machine learning algorithms to detect the avian influenza virus in chickens (Sadeghi et al., 2023). Overall, using sensors in combination with AI algorithms has shown promise in detecting and diagnosing poultry diseases, potentially allowing for earlier intervention and prevention of outbreaks.

Robots in poultry farming

Robots in poultry farming can be seen in various applications, such as automated feeding, egg collection, and environmental control. For instance, robots can collect eggs from hens and transport them to a central location. They can also monitor the birds' behavior, temperature, and humidity in the poultry house (Fei et al., 2023). Furthermore, robots can assist in cleaning the poultry house, reducing the risk of disease transmission among birds (Figure 5).

Ren et al. (2020) provided a comprehensive review of agricultural robotics research, highlighting the machine capabilities that enable intelligent automation of various farm applications. The focus is on Agricultural Intelligent Automation Systems, particularly in poultry production. The review shows that most research in agricultural robotics has focused on perception and reasoning, such as object identification, product quality evaluation, and growth monitoring. However, there is limited published work on task execution and systems integration. The article also reviews agricultural robotics research from 24 universities worldwide and categorizes agricultural robots into monitoring, harvesting, or both functions. Several challenges in robotizing agricultural tasks, including poultry production, are identified, such as environmental monitoring, health assessment, and egg picking. Examples of robotic solutions for poultry production are highlighted, including the OPS robot for sanitizing poultry houses, Poultry Bot for egg picking, and Spoutnic for training hens (Fei et al., 2023).

Robots in poultry farming have several benefits, including increased productivity, reduced labor costs, and improved animal welfare. Robots can save farmers time and money by automating egg collection and cleaning tasks. Furthermore, using robots can reduce the need for human labor, which can be especially useful when labor shortages are a concern. According to a study by Fei et al. (2023), this paper proposes an improved YOLOv5s model for detecting duck eggs in various conditions using a self-developed mobile robot platform. The model incorporates several enhancements, including replacing the backbone feature extraction network with MobileNetV3 for improved speed, introducing the NAM attention mechanism to focus on global information, and utilizing GSConv and BiFPN networks in the Neck layer for efficient multi-scale feature fusion. The Soft-CIoU-NMS algorithm is employed as the bounding box loss function to enhance the detection of dense duck eggs. Experimental results demonstrate that the improved model achieves high accuracy, recall rates, and mAP value compared to the previous version.

Table 1. Different AI-based methods for the identification of various diseases and behaviors of birds

Method for disease identification	AI model	Diagnosed disease or behavior	Importance and hypothecs	Accuracy percentage	Reference
The picture	Support Vector Machine (SVM) model	Bird flu virus	Real-time monitoring of poultry health status with high accuracy, stability, and generalization performance, providing early warning signals for broiler health status	99.469%	Zhuang et al. (2018)
	Machine learning algorithms	Marek's disease	Accurately identify infected birds and help farmers and veterinarians quickly and accurately diagnose and treat diseases in flocks	over 90%	Quach et al. (2020)
	Convolutional Neural Network (CNN) model	Coccidiosis, salmonella, and Newcastle	The MobileNetV2 model is ultimately recommended for deployment due to its lighter weight and better generalization ability	-	Machuve et al. (2022)
The video	The Support Vector Machine (RBF-SVM) model	Newcastle disease virus	The proposed automatic broiler monitoring system provides continuous and non-intrusive early warning and disease occurrence prediction	Accuracies of 0.975 and 0.978, respectively	Okinda et al. (2019)
	Chick Track model	Observation of animal husbandry practices	Improve the welfare of chickens in farming	-	Neethirajan (2022)
The sound	MFCC+Logfbank, the GRU network, the ResNet-50 network	Sex detection method for chicks based on their calls	Significant variations in the sex differences among chick calls across different breeds. The method demonstrates better applicability for three-yellow chicks than native and flaxen-yellow chicks	83% for three-yellow chicks' calls 76.8% for native chicks' calls 66.56% for flaxen-yellow chicks' calls	Li et al. (2022)
	Fisher Discriminate Analysis (FDA) Neural Network Pattern Recognition (NNPR)	*Clostridium perfringens* type A	Detecting and classifying chickens infected with *Clostridium perfringens* type A based on their vocalization	Accuracies of 66.6% on day 16 and 100% on day 22	Sadeghi et al. (2015)
	Convolutional neural network (CNN) models	Identify respiratory diseases in broiler chickens	Identify respiratory diseases in broiler chickens by analyzing their cough sounds	98.4% for detecting infectious bronchitis and 92.6% for detecting Newcastle disease	Mbelwa et al. (2021)
The movement and shape of birds	Trained YOLOv4 object detection model Time-series-based long short-term memory (LSTM) network	Identifying broiler behavior	Identify specific parts of the broiler chicken, construct a chicken skeleton based on these parts, and extract the angle between the backbone fulcrum vectors. Subsequently, broiler behaviors	Average precision, average recall, and F1-score of 82%, 81%, and 81% respectively	Xie and Chang (2022)

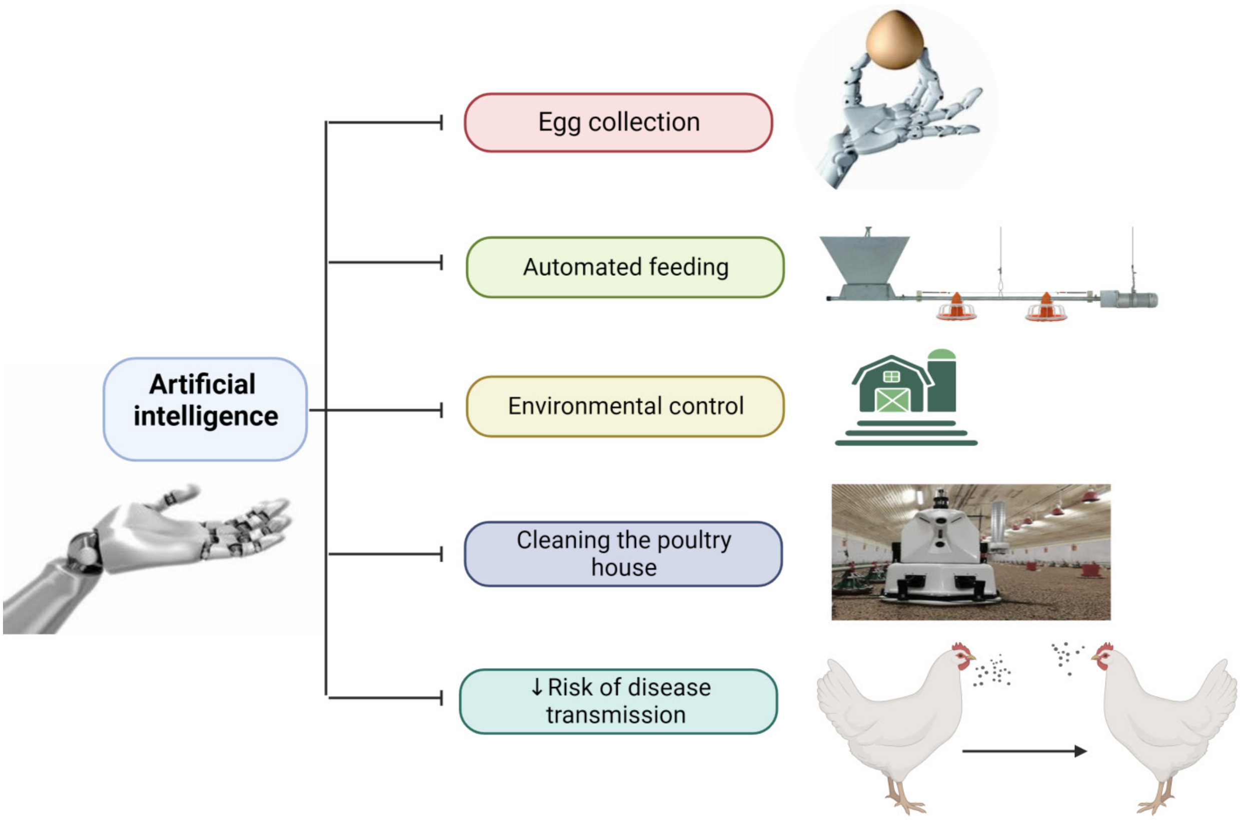


Figure 5. The use of robots in poultry farming in various applications

Robots have the potential to revolutionize poultry farming by increasing productivity, reducing labor costs, and improving animal welfare. As technology advances, we will likely see more robots being developed and deployed in poultry farming. However, further research is needed to determine the long-term impact of robots on poultry production and to address any concerns related to animal welfare and job displacement (Ren et al., 2020).

Conclusion

In conclusion, the use of artificial intelligence and robotics in the poultry industry has proven to be a valuable tool in improving the health and productivity of poultry flocks. Using AI and machine learning, poultry diseases can be identified early, allowing for prompt treatment and minimizing the spread of infection. Using sensors and cameras on robots has allowed for monitoring of the poultry environment, ensuring optimal conditions for growth and development. Furthermore, using robots has increased efficiency in poultry farming by reducing labor costs and improving accuracy in tasks such as feeding and egg collection. The potential for automation and data analysis through AI and robotics can revolutionize the poultry industry, leading to increased profitability and sustainability. Overall, while there are still challenges regarding cost and implementation, the benefits of using artificial intelligence and robotics in poultry farming are clear. Continued research and development in this area are crucial to unlocking the full potential of these technologies for the poultry industry.

Conflict of interest

All authors declare no conflicts of interest that could inappropriately influence this manuscript.

Author contribution

All authors contributed equally to writing this review article. All authors read and approved the final version of this manuscript.

Data availability statement

No data are available.

Acknowledgement

The authors thank their respective institutes and universities for their help.

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Received: 17 XI 2023
Accepted: 4 III 2024