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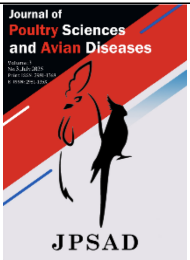

Application of Artificial Intelligence in the Prevention and Diagnosis of Avian Influenza: A Literature Review

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ABSTRACT

Avian Influenza is an important zoonotic viral disease affecting poultry and wild birds. Current prevention and control strategies are often ineffective, leading to significant economic losses and public health risks. This review highlights the role of Artificial Intelligence (AI) and Machine Learning (ML) in enhancing surveillance, early detection, and prediction of avian influenza infections in poultry. Various AI and ML techniques, including Gradient-boosted trees, Convolutional Neural Networks, and Sensor-Based Detection methods, have been applied to classify the pathogenicity of avian influenza virus strains, identify sick and deceased birds, and predict the likelihood of isolating avian influenza viruses in wild bird samples. These innovative solutions can offer high accuracy and efficiency in disease detection, reducing production expenses and enhancing animal welfare. Integrating AI and ML in poultry farming can improve disease management strategies, reduce zoonotic transmission risks, and safeguard global food security. This review provides insights into the current state of AI and ML applications in avian influenza detection and surveillance, highlighting their potential to transform the poultry industry toward a more efficient, sustainable, and healthier future.

Keywords: *Avian Influenza, Machine Learning, Artificial Intelligence, Poultry*

1 Introduction

Avian Influenza is an important viral disease affecting domestic poultry and wild birds. In addition to causing significant damage to the poultry industry worldwide, it can transmit to various animal species and humans (1, 2). Highly Pathogenic Avian Influenza (HPAI) was one of the first viral diseases identified in the early 20th century due to its "filterable" nature (3); however, its close relationship with mammalian influenza viruses was not discovered until 1955 (3, 4). Generally, the term "Avian Influenza" is broadly used to refer to any infection or disease associated with type A influenza viruses. The term "avian influenza viruses" describes type A influenza viruses typically detected in birds (1).

Avian influenza viruses belong to Orthomyxoviridae, genus Influenza virus A (5). Different strains of influenza viruses (A-D) are classified into different genera (commonly referred to as "types") based on serological reactions shown in immunoprecipitation tests and agar gel immunodiffusion (AGID) or gene sequence analysis of the internal segments of the virus (6, 7). Wild waterfowl and other aquatic birds are the primary reservoirs for all type A influenza genes (8). Depending on the pathotype of the avian influenza virus (LP or HP), host characteristics (e.g., age, gender, …), and environmental factors, the clinical symptoms of the disease can substantially vary; however, the clinical signs of the disease are highly variable and depend on other factors such as host species, age, gender, concurrent infections, acquired immunity, and environmental factors (1, 9).

There is no specific and practical treatment for avian influenza in industrial poultry. While using human antiviral drugs like amantadine can reduce mortality in affected flocks (10), it can lead to the development of resistance to these drugs, loss of their effectiveness, and endanger public health (11, 12). The main focus is currently on preventing and controlling highly pathogenic avian influenza outbreaks in industrial poultry flocks. This can be accomplished through timely disease detection, vaccination (13), and culling all affected birds and their biological products (1, 8).

Given the vulnerability of broilers and layer pullets to various diseases and their fragile nature, it is essential to monitor chickens to spot signs of different disorders and prevent potential outbreaks. When depending on labor for farm supervision, a significant rise in the workforce is required to observe the birds closely and regularly, resulting in increased production expenses. Additionally, having more farm workers negatively impacts the environment of poultry and raises concerns about the employees' well-being, as some of these diseases are zoonotic and highly contagious (14). This highlights the significance of incorporating cost-effective solutions. Monitoring technologies such as sensors, cameras, and microphones on poultry farms can substantially reduce human intervention in livestock management. This method enhances system efficiency and detects any diseases or behavioral issues in poultry.

Machine Learning (ML) is a branch of Artificial Intelligence (AI) that can learn and adapt without following explicit instructions. In the last decade, ML has allowed the analysis of complex and large data sets to improve healthcare. Eleven percent of all ML systems that detect microorganisms specialize in parasitic infections (15). ML is used to predict animal health and disease status and has wide-scale applications in animal health, welfare, and veterinary sciences. Understanding the broader context of ML applications within infectious diseases is helpful. ML has proven to be an effective tool for collecting and analyzing large amounts of data in epidemiology and population health.

Furthermore, it is useful for predicting outbreaks of diseases, as well as for performing disease surveillance. Additionally, ML is employed in the diagnosis and management of diseases, the recognition of behaviors, the management of the environment, and the evaluation of livestock growth (16-18). AI is increasingly used in digital pathology for tissue and cytological sample analysis and for storing and archiving cytological images. In this review article, we highlight some of the practical applications of ML in detecting and surveilling Avian influenza (19).

1.1 Fundamentals of Neural Network

In supervised learning, the computer receives training data along with known output values. In essence, the goal is to learn general rules (also called models) that map inputs to outputs so that the output can be predicted for unseen data with inputs that have been observed but no outputs. Supervised learning algorithms include Support Vector Machines (SVMs), boosted trees, and linear discriminant analyses (LDAs). Models for avian influenza are based on neural networks, which are included in supervised learning (20-23).

With learning models, neural networks perform well when learning difficult tasks. Their use is growing across various fields, including infectious disease diagnosis and computer vision. Much like neurons in the brain, simple processors (neurons) in neural networks are heavily interconnected. They can function as distributed or massively parallel computers because of their inherent nature, which enables them to accelerate complex optimization tasks. The network mimics the human brain by learning, thinking, and acting by combining the states of neurons. Neural networks have an input layer, a hidden layer, and an output layer. Input layers receive the initial data. Hidden layers perform intermediary computations. To form feature hierarchies, higher-level features are combined with lower-level features. As neural networks have multiple hidden layers, they can learn complex patterns and data representations. The output layer produces the neural network's final prediction (20, 23-25).

This study aims to investigate the integration of artificial intelligence, with a particular emphasis on machine learning and image processing techniques, in diagnosing and treating avian influenza.

2 Material and Methods

A literature search was conducted on October 3, 2023, across multiple electronic databases, including PubMed, Scopus, Web of Science, ResearchGate, Google Scholar, Elsevier, Scientific Information Database (SID), MagIran, and IranDoc. The search strategy employed a combination of keywords: "Machine Learning," "Artificial Intelligence," "Avian Influenza," and "poultry," adapted to the specific configurations of each database, with no restrictions on publication date. English keywords were utilized for PubMed, Scopus, Web of Science, and ResearchGate, while both English and their Persian equivalents were applied for Google Scholar, SID, and MagIran. All identified records from Persian keyword searches in Google Scholar, along with the first 100 English-language results sorted by the most relevant, were extracted. The remaining databases were comprehensively searched, and all results were retrieved.

The extracted records were imported into an EndNote library, where duplicate entries were identified and removed, retaining unique citations. Two independent reviewers conducted a preliminary screening of titles and abstracts to assess eligibility based on predefined inclusion and exclusion criteria. Studies were included if they investigated AI-based methodologies for diagnosing or preventing avian influenza in poultry. Exclusions comprised articles lacking direct relevance to the search terms, those providing generalized or non-technical overviews of the topics, and publications deemed methodologically insufficient or lacking academic rigor.

Following an initial screening, among 35 scientific articles, only 15 articles met the eligibility criteria. Discrepancies between reviewers regarding article inclusion were resolved through deliberative discussion to achieve consensus. The 15 selected articles were carefully examined, and the key points of each were extracted. Considering the content of the discussion, all articles were reclassified, and the key points and discussion topics were integrated into the article's main text. This process ensured alignment with the research focus on AI-driven approaches to avian influenza management, prioritizing empirical studies with methodological coherence and applied relevance.

3 Results

Utilization of Artificial intelligence in avian influenza diagnosis

In the results section, all selected articles were categorized according to the research methodology employed in their respective studies. It should be noted that some of these articles are unique due to their methodological approach and the novelty of their research topic, with no analogous counterparts existing in the literature. The table below organizes articles that employ artificial intelligence for the early detection and diagnosis of avian influenza. It includes the publication year, authors' names, and the methods used (Table 1).

Table 1. Artificial intelligence (AI) is utilized in the early detection and diagnosis of avian influenza, sorted by the year of the publication, author's name, and integrated AI architecture.

Reference	Author(s)	Date	AI Technique(s)
(26)	Duan C, et al.	2023	Gradient-boosted trees, ML-driven surveillance strategies
(27)	Chadha A, et al.	2023	Logistic Regression (LR), Random Forest (RF), KNN, Naïve Bayes (NB), SVM, CNN
(28)	González-Recio O, et al.	2014	Machine Learning (ML) methods for genome-wide prediction (e.g., SVM, RF)
(29)	Huang J, et al.	2019	Sound analysis (Fast Fourier Transform, Discrete Wavelet Transform)
(30)	Bao Y, et al.	2021	Machine Learning (ML) algorithms for classification
(31)	Walsh DP, et al.	2019	Gradient-boosted trees, ML for viral isolation prediction

(32)	Rizwan M, et al.	2016	Audio signal processing (unspecified ML) for rale sound detection
(33)	Sadeghi M, et al.	2023	Thermography with SVM, ANN, and Dempster-Shafer evidence theory
(34)	Banakar A, et al.	2016	Data-mining, Dempster-Shafer theory for sound-based disease diagnosis
(35)	Gulyaeva M, et al.	2020	Data mining, GIS, predictive modeling for LPAIV/HPAIV co-circulation
(36)	Yoo DS, et al.	2022	Random Forest (RF), Gradient Boosting Machine (GBM), XGBoost
(37)	Orandi JA, et al.	2023	Convolutional Neural Networks (CNNs) for posture-based detection
(38)	Valletta JJ, et al.	2017	Machine Learning (ML) applications in robotic surveillance
(39)	Astill J, et al.	2018	Surveillance technologies, Big Data analytics, and ML for outbreak prediction
(40)	Mbelwa H, et al.	N/A†	Deep Convolutional Neural Networks (CNNs), XceptionNet (pre-trained)

3.1 Surveillance and early detection of HPAI

The recent outbreaks of HPAI in wild birds have underscored the critical need for effective surveillance and early detection of this virus. To address this challenge, ML has emerged as a powerful tool for predicting the likelihood of isolating AIVs from wild bird surveillance samples. Gradient-boosted tree algorithms have proven to be particularly well-suited to this task, enabling us to explore the importance of various features for predicting the probability of AIV isolation and develop a model with high predictive power. Interestingly, some findings suggested that several traditional features used in wild bird surveillance, such as age, sex, and type of bird sampled, may not be as important as previously thought. This highlights the potential for ML to uncover novel insights and help identify features deemed of higher importance for predicting AIV isolation. By removing the less significant features, such as age, sex, and type of bird sampled, these studies were able to simplify their model without compromising its predictive power. Furthermore, these approaches have the potential to be used to predict AIV isolation in other species, as well as in other contexts (26, 41).

3.2 Predictive analysis for pathogenicity classification of H5Nx avian influenza strains

Various approaches can be used to infer the virulence and pathogenicity of H5Nx avian influenza strains in poultry, often involving identifying specific pathogenicity markers in their hemagglutinin (HA) gene. Predictive modeling techniques offer a promising method to explore the relationship between genetic characteristics and disease severity, aiding experts in assessing the pathogenicity of circulating AI viruses. A study aimed to evaluate different ML methods for predicting the pathogenicity of H5Nx viruses in poultry using complete HA gene sequences (27). Among 2137 annotated H5Nx HA gene sequences, 46.33% were classified as highly pathogenic (HP) and 53.67% as low pathogenic (LP) based on the presence of the polybasic HA cleavage site (HACS). By employing various ML classifiers such as Logistic Regression (LR), Random Forest (RF), K-nearest Neighbor (KNN), Naïve Bayes (NB), Support Vector Machine (SVM), and Convolutional Neural Network (CNN), the study achieved approximately 99% accuracy in classifying pathogenicity through a 10-fold cross-validation approach. The results indicate that ML techniques can effectively classify H5 virus pathogenicity, with LR (L1/L2), KNN, SVM (RBF), and CNN classifiers showing the highest accuracies for aligned DNA and protein sequences. These findings suggest the potential of ML methods in routinely classifying the pathogenicity of H5Nx avian influenza viruses in poultry, especially when characteristic markers are present in the dataset (42).

3.3 Sensor-based Detection method

Numerous approaches exist for identifying deceased and unhealthy chickens using sound and image data, though they often fail to achieve optimal outcomes (29). A new study introduces a novel sensor-based detection method leveraging AI (30). The first step of this approach is measuring the maximum displacement of chicken movements by attaching a foot ring to each chicken and calculating the three-dimensional total variance to indicate activity intensity. After that, the detection terminal gathers data from the foot rings via a ZigBee network. ML algorithms are employed to classify the state of the chickens (alive, deceased, or unhealthy). This fusion of AI and sensor technology boasts high detection accuracy and brings about cost savings in operations. Practical trials reveal a system accuracy of 95.6% in identifying deceased and unhealthy chickens, with a 25% reduction in operating costs over four years compared to manual methods. This method can be used in the early detection of HPAI.

3.4 Geographical Location and rRT-PCR as Key Predictors

It has been applied to gradient-boosted trees, a type of ML, to assess the likelihood of detecting AIV in wild bird samples gathered during AIV surveillance conducted in the United States between 2006 and 2011. This analysis considered age, gender, bird species, location, and rRT-PCR results for the matrix gene. The finalized model demonstrated strong predictive capabilities and identified geographical location and rRT-PCR outcomes as key predictors. The model indicated higher probabilities of viral isolation in samples from the north-central states and the southeastern region of Alaska. Lower rRT-PCR Ct-values corresponded to a higher chance of AIV isolation, with the model estimating a 16% probability of detecting AIV in samples previously considered negative (Ct-value ≥35) according to the rRT-PCR screening test and standard protocols. This model can prioritize existing samples for isolation and efficiently assess AIV surveillance strategies to enhance the chances of viral detection within resource limitations and laboratory capacities (31).

3.5 Early Detection Utilizing Thermography and Artificial Intelligence

Non-invasive methods play a crucial role in precision farming for poultry, aiding in reducing stress and enabling ongoing monitoring (32). Poultry behavior can provide insights into their physical and mental well-being and overall health. Early detection of issues triggers timely actions. Sadeghi et al. utilized thermal imaging and ML to detect avian diseases (33). They studied four groups of 14-day-old Ross 308 Broilers (20 birds in each group). Two groups were deliberately infected with Newcastle Disease (ND) or Avian Influenza (AI), while the other two served as control groups. Thermal images were taken every 8 hours and analyzed using MATLAB. Following denoising and background removal, 23 statistical features were extracted, with the most relevant ones identified using an enhanced distance evaluation technique. Support Vector Machine (SVM) and Artificial Neural Networks (ANN) were utilized as classifiers, with SVM proving more effective in disease identification. All features with scores of 0.7 or higher were favorable for classification as Avian Influenza because there was a significant difference between 0.7 and other lower threshold limits in this study. When both classifiers fell short in accuracy, the Dempster-Shafer evidence theory was applied for data fusion. The final SVM-based system achieved impressive accuracy rates of 97.2% for AI and 100% for ND classification within 24 hours post-infection. This novel approach presents a valuable method for promptly recognizing avian diseases and facilitating early intervention measures. While this study demonstrates promising accuracy in AI-driven thermography for avian disease detection (97.2% for AI, 100% for ND), the limited sample size (n=20 per group), controlled infection conditions, and reliance on specific feature thresholds (e.g., 0.7) necessitate further validation in diverse, large-scale poultry populations.

3.6 Detecting Avian Diseases with Sound Signals

In the quest to improve poultry health, Banakar et al. have developed an automated disease detection system that benefits both production efficiency and animal welfare. Their intelligent device uses data-mining techniques and Dempster-Shafer evidence theory (D-S) to diagnose avian diseases. The study involved 14-day-old chickens divided into four groups: those deliberately infected with Newcastle Disease (ND), Infectious Bronchitis Virus (IBV), and Avian Influenza (AI), along with a control group. By analyzing chicken sounds using the Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT), this innovative approach holds promise for early disease detection in poultry farming. Twenty-five statistical features from frequency domains and 75 from time-frequency domains were extracted. The most relevant sound signal features were selected using an improved distance evaluation (IDE) method. Chicken sounds were analyzed over two consecutive days after the virus infection. The breakthrough came with the D-S infusion of sound data, resulting in an impressive accuracy of 91.15% (34).

3.7 Harmony and Hazards: Relation between Avian Influenza Viruses

Co-circulation of avian viruses between low-pathogenic avian influenza viruses (LPAIVs) and high-pathogenic avian influenza viruses (HPAIVs) suggests their interactions in their ecological aspects. This hints at intriguing ecological interactions. Researchers took an international approach, focusing on the Pacific Rim. Gulyaeva et al. conducted data mining and used predictive modeling and ML alongside open-access datasets and geographic information systems (GIS). Zooming in on 5 km pixels, patterns have been discovered based on 157 hosts and 110 LPAIVs across 32 species. Notably, Muscovy ducks, Mallards, Whistling Swans, and gulls dominated LPAIV prevalence, emphasizing the industrial impact on the human-dominated wildlife contact zone (35).

3.8 Predicting HPAI infections at individual poultry holdings

Adapting the complex dynamics of transmission mechanisms and providing real-time risk estimation is challenging. Dae-sung Yoo et al. introduced a continuous risk prediction framework for predicting HPAI occurrences using machine learning algorithms (MLAs) to address this. This framework integrated data sources such as environmental, on-farm biosecurity, meteorological, vehicle movement tracking, and HPAI wild bird surveillance data to enhance accuracy and timeliness. The process involved generating 1788 predictors from six types of data, organizing them alongside an outcome variable in a data mart based on a temporal assumption, training these predictors with the outcome variable during the 2016–2017 HPAI epidemic, and using three MLAs (Random Forest, Gradient Boosting Machine, and eXtreme Gradient Boosting) to predict daily HPAI infection risks during the 2017–2018 epidemics. The models successfully identified 8–10 out of 19 high-risk infected premises in advance during the outbreak period. The Gradient Boosting Machine MLAs performed exceptionally well predicting HPAI infections at individual poultry holdings, achieving an AUC (area under the curve) of 0.88 for 7-day forecasting. This method improves the flexibility and timing of interventions against HPAI outbreaks on poultry farms (36).

3.9 A Computer Vision System For Early Detection Of Sick Birds In A Poultry Farm Using Convolution Neural Network On Shape And Edge Information

This research aimed to create a computer vision system that quickly identifies sick birds on a poultry farm, utilizing Convolutional Neural Networks (CNNs) to evaluate shape and edge features. This was accomplished by assembling a labeled dataset of sick and healthy birds. Training various models aimed to determine which features could most accurately predict a hen's health status based on its appearance. It was assumed that sick hens typically exhibit downward-stooping wings and tails and a weak neck that bends downwards. Images were captured using a camera and incorporated into four convolutional neural network models. Three of these models were developed using specific features extracted (ridges, edges, and Harris corners), while the fourth model was trained on the complete image without excluding any features. The models were then evaluated based on their predictive accuracy.

The models were assessed based on their performance during training and their effectiveness on unseen data. The model utilizing Harris corners achieved the highest accuracy at 94.14%, whereas the model using the full set of features attained the lowest accuracy of 46.66%, respectively. The Harris corners model was subsequently used to create a web-based system to predict the health status of hens on a poultry farm. This study successfully met its goal and demonstrated that it is feasible to classify healthy and sick birds based on a single feature (37).

3.10 Robotic Surveillance

In addition to traditional surveillance methods involving monitoring poultry through digital means, robotics has emerged as a potential tool for early disease detection. Several companies have developed robots designed to operate within poultry facilities, fulfilling various functions (38). These robots, typically autonomous small vehicles, can improve barn sanitation, boost chicken activity, and perform other tasks. One key function they can carry out is identifying severely ill or deceased chickens. Equipped with mounted cameras to capture multiple images quickly, these robots can identify unresponsive poultry that may be sick or deceased. This early detection capability allows for the prompt removal of avian influenza and other infectious diseases that have affected animals and investigation into the cause of death. By utilizing robots like these, the need for human monitoring of poultry for illness can be reduced, thereby lowering the risk of introducing infectious agents into the poultry facility.

3.11 Introducing the best pre-trained CNNs for Chicken Diseases Detection: XceptionNet

With the efforts of Hope Mbelwa et al., a deep learning approach has been presented utilizing Convolutional Neural Networks (CNNs) to determine whether chicken feces fall into one of the three categories defined by the model. Pre-trained models have also been utilized to solve the same issue. The comparison demonstrates that the model based on XceptionNet outperforms all other models across all evaluated metrics. Experimental results indicate a clear advantage of transfer learning, with a validation accuracy of 94% for the pre-trained model, compared to 93.67% for the fully trained CNNs developed on the same dataset. Overall, the fully trained CNNs rank second compared to the other model. These findings suggest that the pre-trained XceptionNet method delivers superior performance and the highest prediction accuracy, making it well-suited for applications in chicken disease detection (40).

4 Discussion

This review sought to assess the existing and prospective uses of AI, with a particular focus on ML, in diagnosing and monitoring avian influenza within poultry populations. Our findings indicate that AI methodologies have demonstrated considerable potential to enhance early detection, facilitate real-time monitoring, and develop predictive models for outbreaks. ML algorithms have been successfully utilized for diagnostics based on imaging, interpretation of genomic data, and risk assessment mapping. Nevertheless, despite significant progress, challenges such as data quality, model interpretability, and the necessity for interdisciplinary collaboration continue to pose significant obstacles to wider implementation.

In 2023, the financial turnover of artificial intelligence in animal health reached 1.2 billion dollars (28, 43). Utilizing this financial flow to improve health and poultry farming can contribute to the growth of the AI market and its ancillary products, advance the goals of poultry-related industries, and enhance global food security. Infectious bronchitis, coccidiosis, Newcastle disease, and salmonellosis have received more attention due to their significant economic impact and persistent occurrence in avian populations. These diseases, which manifest through changes in fecal appearance, body temperature, egg quality, and bird movement within the facility, can be clinically diagnosed using data collected from the facility environment. For instance, in the case of coccidiosis, where assessing infection severity relies on determining the number of sporulated oocysts in fecal samples, designing an AI-based automated model for oocyst counting can enhance speed and accuracy in detecting contamination levels and identifying accessible species (44). Additionally, datasets based on fecal variations in coccidiosis, Newcastle disease, and salmonellosis have been developed to achieve high-precision diagnosis (45).

Using surveillance technologies and advanced analytical tools such as ML enables the extraction of valuable insights from complex data related to large poultry populations, offering crucial information about their health and infection status. Analyzing subtle changes in vocalization, activity, and physiology makes it feasible to detect poultry infections and diseases. These surveillance methods enable real-time tracking of poultry, facilitating the early identification of health issues. Additionally, point-of-care devices will enable swift determination of the presence of infectious diseases. This combination of early detection and rapid diagnostics empowers producers to respond promptly to infectious disease scenarios, reducing losses and preventing the spread of infections among birds. By minimizing the transmission of infectious agents within poultry, there is also a potential decrease in the risk of zoonotic transmission to humans, thereby mitigating the threat of outbreaks associated with the projected intensification of poultry production in the future (39).

The application of artificial intelligence in avian influenza diagnosis encompasses diverse methodologies, each presenting distinct advantages and limitations. Supervised learning techniques, such as gradient-boosted trees, demonstrate high predictive power and feature prioritization, enabling model simplification and cross-species applicability. However, their relegation of traditional variables like age and sex may challenge established surveillance paradigms. Predictive pathogenicity classification via ML classifiers achieves near-perfect accuracy by leveraging genetic markers like polybasic HACS yet risks overfitting and reduced generalizability in marker-absent contexts. Sensor-based systems offer real-time, cost-efficient monitoring with high operational accuracy but face sensor dependency and data transmission reliability constraints. Geographical and rRT-PCR models enhance sample prioritization under resource limitations but exhibit geographical specificity and modest predictive probabilities for PCR-negative samples. Non-invasive approaches, such as thermography and sound analysis, enable stress-free early detection with high accuracy yet require controlled environmental conditions and complex feature extraction. Ecological data mining elucidates host-virus interactions through GIS but is limited by regional data granularity and dataset completeness. Risk prediction frameworks integrate multimodal data for real-time forecasting with robust AUC performance but demand computational intensity and continuous data streams. Computer vision systems achieve high diagnostic accuracy via feature-specific CNNs, though their reliance on postural cues introduces variability in image-based generalization. Robotic surveillance reduces zoonotic risks through automation but incurs high infrastructural and maintenance costs. Finally, pre-trained CNNs like XceptionNet optimizes disease detection via transfer learning, yet depend on image quality and may lack scalability for emerging pathologies.

Collectively, these methods balance innovation with practical constraints, underscoring the need for context-adaptive solutions in AI-driven avian influenza management.

However, due to the unique nature and pathogenicity of avian influenza viruses, research efforts in preventing and diagnosing this disease often focus on laboratory-based detection using artificial intelligence. So far, the ability to accurately diagnose avian influenza at the farm level has not been fully realized. Clinical diagnosis of highly pathogenic avian influenza (HPAI) remains challenging for experts in the poultry field due to the rapid spread of the disease and high mortality rates among birds even before clinical symptoms appear. In contrast, low pathogenic avian influenza (LPAI), which exhibits greater clinical diagnostic capabilities than HPAI and allows for creating large datasets for various bird species (35), still requires further targeted research in this area.

5 Future and prospects

Artificial intelligence has become one of the most important technologies, and it is crucial that functional applications be developed that can benefit our daily lives and our careers. Diagnosis of avian influenza is not an exception, and the first steps of this path have been taken. As a result of recent developments, it is now easier to produce artificial intelligence-based applications with fewer datasets and higher accuracy. The transfer learning method, for example, is an efficient way of developing AI applications without integrating many datasets. Combined with integrating models and trained data, the dataset volume will be dramatically reduced (46).

6 Conclusion

Avian influenza is a significant viral disease affecting both domestic poultry and wild birds, potentially spreading to other animal species and humans. Current efforts focus on preventing and controlling HPAI outbreaks in industrial poultry through methods such as vaccination and culling. Advanced technologies like artificial intelligence, machine learning, and sensor-based detection methods are being leveraged to enhance surveillance, early detection, and predicting avian influenza infections in poultry. These technologies offer high accuracy in identifying sick and deceased birds, predicting the pathogenicity of avian influenza strains, and classifying the likelihood of isolating avian influenza viruses in wild bird samples. Using deep learning for disease classification in chickens aligns with an emerging trend where deep learning techniques find application across various agricultural tasks. This trend has the potential to significantly transform the livestock industry, impacting areas such as disease detection and yield forecasting (47).

Incorporating AI into avian influenza diagnosis and prevention offers transformative benefits, including enhanced surveillance frameworks, predictive accuracy, and early detection capabilities. Machine Learning algorithms, such as gradient-boosted trees and Convolutional Neural Networks (CNNs), enable rapid analysis of complex datasets—ranging from genomic sequences to thermal imagery—facilitating real-time pathogenicity classification, outbreak prediction, and identification of high-risk geographical zones. AI-driven sensor systems and robotic surveillance automate non-invasive monitoring of poultry health, reducing reliance on labor-intensive methods while improving operational efficiency and cost-effectiveness. Predictive modeling optimizes resource allocation by prioritizing high-probability viral isolates and refining surveillance strategies under laboratory constraints. Additionally, AI can uncover non-traditional epidemiological markers, synthesize multimodal data (e.g., environmental, behavioral, and acoustic signals), support adaptive biosecurity protocols and preemptive interventions, and mitigate economic losses and zoonotic transmission risks. By transforming raw data into actionable insights, AI enhances diagnostic precision, accelerates response timelines, and strengthens global preparedness against avian influenza outbreaks. In an overview, by integrating AI and ML techniques in poultry farming, producers can improve disease management strategies, reduce production expenses, enhance animal welfare, and safeguard public health against zoonotic transmission risks. The continuous development and application of these innovative solutions in poultry health monitoring are crucial for the early detection of avian diseases and prompt intervention measures, ultimately safeguarding global food security and advancing the poultry industry toward a more efficient, sustainable, and healthier future (48).

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Conflict of Interest

All authors declare that they have no conflicts of interest.

Author Contributions

All authors contributed to the original idea and study design.

Data Availability Statement

Data are available from the 1st and the last (corresponding) author upon reasonable request.

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