Title: Applications of artificial intelligence in avian radiology: A systematic review of disease diagnosis, image interpretation, prognosis, and implementation challenges in veterinary and wildlife medicine

Running Title: Applications of AI in avian radiology

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Abstract

Recent advances in artificial intelligence (AI) and deep learning have revolutionized medical image processing. Artificial intelligence is transforming all aspects of modern veterinary medicine, increasing the accuracy, speed, and efficiency of animal healthcare. However, the primary focus of AI has so far been on human medicine, and its applications in veterinary medicine, especially in the specialized field of avian radiology, have been less systematically investigated. This systematic review aims to summarize the available evidence and analyze the current role and future potential of AI in avian radiology. A systematic search of the PubMed, Scopus, Web of Science, and Google Scholar databases was conducted for studies published between January 2020 and January 2026. Keywords included combinations of "artificial intelligence," "machine learning," "radiology," "diagnostic imaging," "birds," "poultry," and "veterinary medicine." Inclusion criteria were primary studies that specifically addressed the use of AI algorithms for interpreting radiological images (e.g., radiography, CT scans) across different avian species. Of the 257 studies identified, 21 met the inclusion criteria. The analyses show that AI applications in avian radiology are mainly focused on four areas: 1) automated disease diagnosis (e.g., pneumonia, ascites, joint dislocation, foreign body detection), 2) segmentation of anatomical structures and lesions (e.g., accurate determination of heart, liver, or pathological masses), 3) prognostic prediction (e.g., assessment of response to treatment in chronic diseases), and 4) image quality enhancement. Most of the developed algorithms were based on convolutional neural networks (CNN) and focused on chest and abdominal radiography of domestic (ornamental) and industrial poultry. The reported accuracy in studies for specific diagnostic tasks was often above 90%, indicating the high potential of this technology. Artificial intelligence is emerging as a powerful adjunct tool in avian radiology, increasing the accuracy, speed, and objectivity of image interpretation. AI has significant potential to assist general veterinarians and specialized radiologists. However, significant challenges, including limited access to large, well-annotated databases (data limitations), wide anatomical variation across avian species, and the need for validation in real clinical settings, have hindered widespread deployment of this technology.

Keywords: Artificial intelligence, Birds, Deep learning, Disease diagnosis, Radiology

1. Context

The poultry industry, as well as the care of domestic and wild birds, plays a vital role in food security, the economy, and biodiversity conservation [1-5]. In this context, diagnostic imaging, particularly radiology, has become an essential component in diagnosing diseases, assessing injuries, and monitoring bird health [6, 7]. However, interpreting radiological images in birds poses unique challenges. The incredible diversity in size and anatomical morphology across species, from domestic chickens to ornamental parrots and birds of prey, requires in-depth specialist knowledge [8]. In addition, physiological differences, such as the presence of air sacs, complicate the interpretation of lesions. These factors make radiographic analysis often time-consuming and, at the same time, somewhat dependent on the radiologist's experience and subjective judgment, leading to discrepancies in diagnoses between specialists [9].

Artificial intelligence is transforming all aspects of modern veterinary medicine, increasing the accuracy, speed, and efficiency of animal healthcare [10]. In diagnostics, deep learning algorithms can analyze medical images such as radiographs, ultrasound images, and pathology slides with accuracy comparable to, or even exceeding, that of human experts, and can detect small tumors, hairline fractures, or metastases in their early stages [11]. The technology also plays a vital role in preventive medicine, where big data and predictive models can be used to forecast the spread of infectious diseases across large herds and prevent significant economic losses through timely intervention [12]. In addition, smart devices equipped with computer vision and wearable sensors allow for continuous monitoring of vital signs, behavioral patterns, and even pain and stress levels in animals, providing veterinarians and animal owners with early warnings of emerging health problems [13]. AI has even penetrated the field of surgery, where AI-guided robotic systems help surgeons perform more precise, minimally invasive procedures and shorten animal recovery times. Ultimately, by personalizing treatment and health management, from pets to large livestock populations, this technology will not only improve the quality of life of animals but also contribute to the sustainability and productivity of the livestock industry and even the public health of humans (through the control of zoonotic diseases and even pandemic prevention) [14-16].

In recent years, the revolution in AI, particularly its leading branch, deep learning, has pushed the boundaries of medical and veterinary science (Figure 1). In medicine, AI algorithms are now being used as efficient assistants in screening, diagnosing, and even predicting disease outcomes from radiological images [17]. By learning from thousands of annotated images, these systems can identify subtle patterns and quantify image features that may be hidden from the human eye [18, 19]. This potential raises the fundamental question of whether AI can address the challenges facing avian veterinary radiology and revolutionize the accuracy and efficiency of diagnosis in this field [20-23].

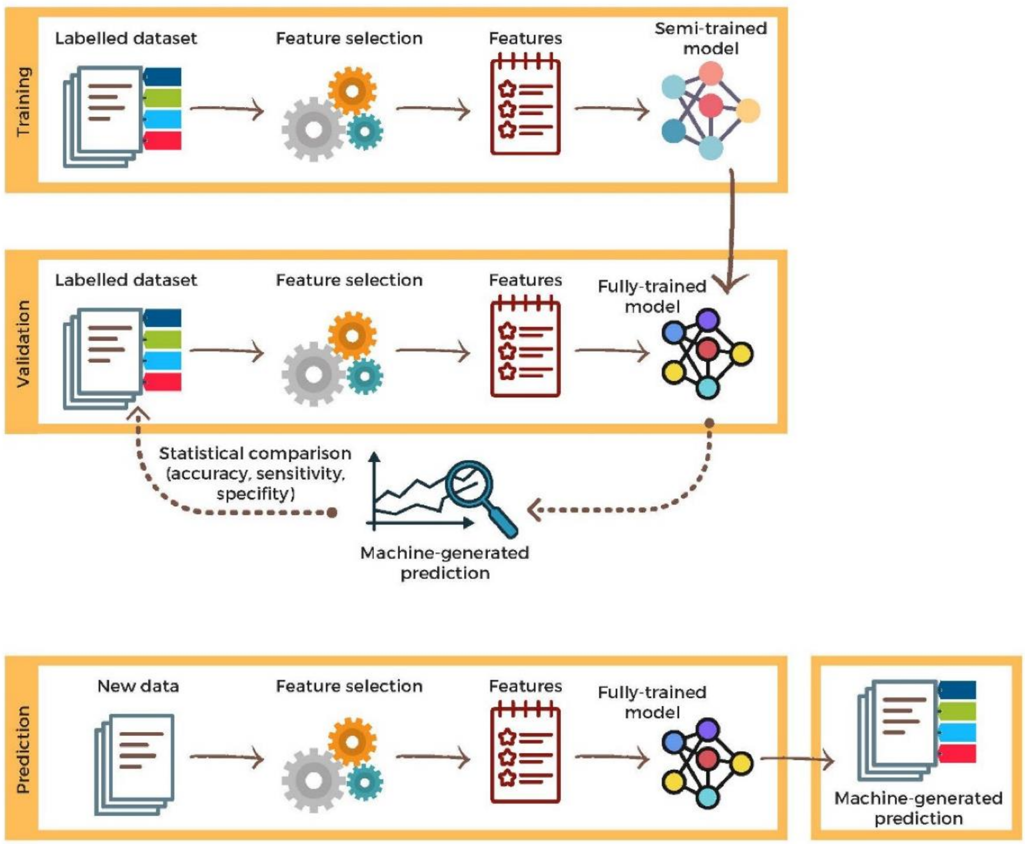

Figure 1. A brief description of supervised learning flowchart, including training, validation, and prediction (MDPI Copyright, 2022) [24].

Although interest in automation and computer assistance in agriculture and veterinary medicine is growing, the existing research literature on the application of AI in avian radiology is sparse and limited primarily to proof-of-concept studies for specific species or diseases [25]. The lack of a systematic review that provides a comprehensive picture of the current status, practical applications, success rates, and barriers to this emerging technology is clearly evident (Figure 2). This gap prevents the veterinary community from fully understanding AI's true capabilities and from guiding future research in the most effective directions (Figure 3).

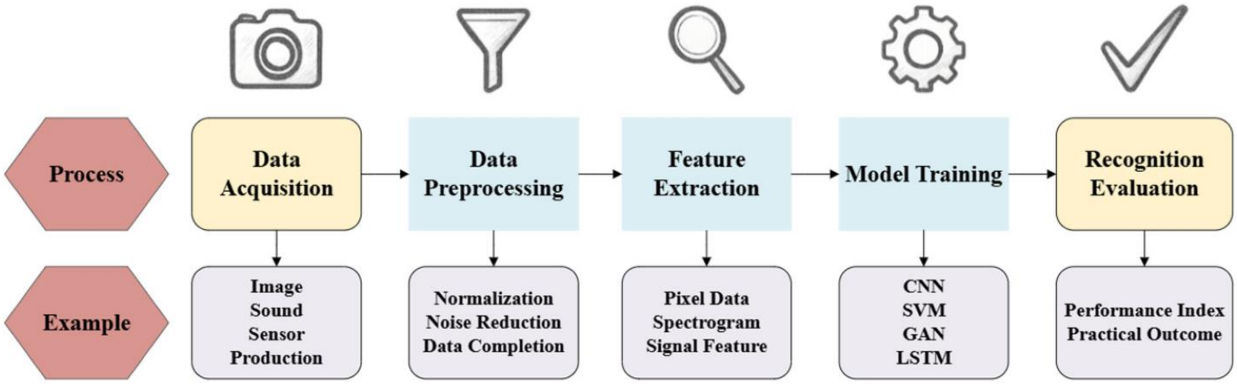

Figure 2. AI data processing workflow in chicken farming. CNN: Convolutional Neural Network; SVM: Support Vector Machine. GAN: Generative Adversarial Network; LSTM: Long Short-Term Memory (MDPI Copyright, 2025) [26].

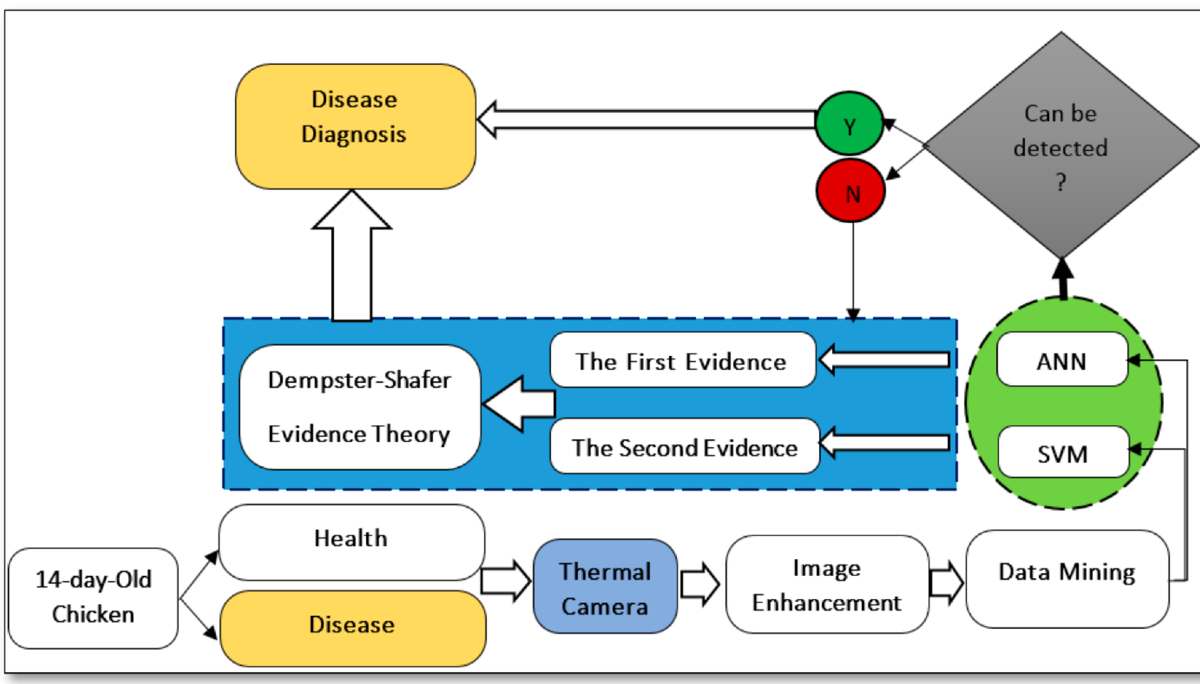

Figure 3. Proposed algorithm framework to identify avian diseases. ANN is artificial neural network, and SVM is support vector machine (MDPI Copyright, 2023) [27].

The primary goal of this systematic review is to collect, evaluate, and critically synthesize all available scientific evidence on the use of AI algorithms in avian radiological image analysis. This study intends to carefully analyze these studies to clearly delineate the role of AI in key diagnostic radiology tasks, including automated disease diagnosis (e.g., pneumonia, ascites, or fractures), segmentation and measurement of anatomical structures (e.g., viscera), and image quality enhancement.

2. Data Acquisition

This systematic review was designed and conducted in accordance with the Preferred Reporting Items for Systematic Reviews (PRISMA 2020) guidelines to identify, evaluate, and synthesize all studies related to the use of AI in avian radiology. The primary focus was on studies published or available between January 2020 and January 2026.

2.1. Search strategy and information sources

To conduct a comprehensive and systematic search, a structured search strategy was designed between January 2020 and January 2026 in consultation with a medical informatics expert. The search was conducted in central and international databases, including PubMed/MEDLINE, Embase, Scopus, Web of Science Core Collection, and IEEE Xplore. To maximize coverage and include grey literature and studies published in specialized veterinary journals, a search also be completed in Google Scholar. Only English studies were included. Keywords and terms were defined using a combination of controlled terms (such as MeSH in PubMed and Emtree in Embase) and free terms in the main fields of "artificial intelligence", "diagnostic imaging", "birds", and "veterinary". An example of such a combination is: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "computer-aided diagnosis") AND ("radiography" OR "diagnostic imaging" OR "tomography" OR "x-ray") AND ("bird*" OR "avian" OR "poultry" OR "fowl") AND ("veterinary" OR "animal").

2.2. Study selection and screening criteria

Study selection was based on the PICOS (Population, Intervention, Comparison, Outcome, Study design) framework as follows:

Population (P): Studies that focus on radiological images (including radiography, CT scan, fluoroscopy, ultrasound) from any bird species (industrial poultry such as chickens, turkeys; domestic birds; wild birds or wildlife).

Intervention (I): Development, training, validation, or application of an AI, machine learning, or deep learning algorithm (such as convolutional neural networks) to automatically analyze these images. This analysis could include disease diagnosis, segmentation of anatomical structures, image classification, or image quality enhancement.

Comparison (C): The presence of a reference standard for evaluating algorithm performance, such as the interpretation of one or more veterinary radiologists, necropsy findings, or definitive laboratory results.

Outcome (O): Reporting of at least one quantitative measure of diagnostic or analytical performance, such as accuracy, sensitivity, specificity, area under the ROC curve (AUC), or similar measures.

Study design (S): All primary studies (cross-sectional, cohort, case-control) and predictive modeling studies reporting primary data. Review studies, theoretical articles, conference abstracts without full text available, and studies lacking an appropriate reference standard or quantitative assessment of performance will be excluded.

2.3. Study selection and screening process

All search results were entered into reference management software (EndNote), and duplicates were removed. The screening process was conducted in two stages by two independent reviewers based on the title and abstract (stage 1) and then the full text of the articles (stage 2), in accordance with the PICOS criteria. Any disagreements between reviewers are resolved through discussion and, if necessary, by a third reviewer's vote. The reasons for excluding each study during the full-text screening stage were recorded and reported. The overall flow of study selection was outlined and presented in a PRISMA diagram. In addition to the initial search, a literature review of relevant review articles and selected final studies was conducted to identify additional sources and ensure that all relevant evidence has been identified between January 2020 and January 2026.

2.4. Data extraction

Data from the final eligible studies will be extracted by two independent reviewers using a standard data extraction form designed prior to the study. This form included sections such as general study characteristics (authors, year, country), methodological characteristics (study type, number and species of birds, imaging type), AI algorithm characteristics (model type, architecture, training/test dataset), key results (performance metrics such as accuracy, AUC, sensitivity, specificity), and principal conclusions.

2.5. Data synthesis and analysis

Given the expected heterogeneity of the studies (in terms of bird species, diseases investigated, types of algorithms, and reported measures), a descriptive qualitative synthesis is considered the main approach to synthesize the evidence. The findings were categorized and summarized in tables and text, structured around the main AI applications (detection, segmentation, prediction), the types of algorithms used, and the species studied.

3. Results and Discussion

Of the 257 studies identified, 21 met the inclusion criteria (Figure 4). The analyses show that AI applications in avian radiology are mainly focused on four areas: 1) automated disease diagnosis (e.g., pneumonia, ascites, joint dislocation, foreign body detection), 2) segmentation of anatomical structures and lesions (e.g. accurate determination of heart, liver, or pathological masses), 3) prognostic prediction (e.g. assessment of response to treatment in chronic diseases), and 4) image quality enhancement [22, 25, 28-32]. Most of the developed algorithms were based on convolutional neural networks (CNN) and focused on chest and abdominal radiography of domestic (ornamental) and industrial poultry.

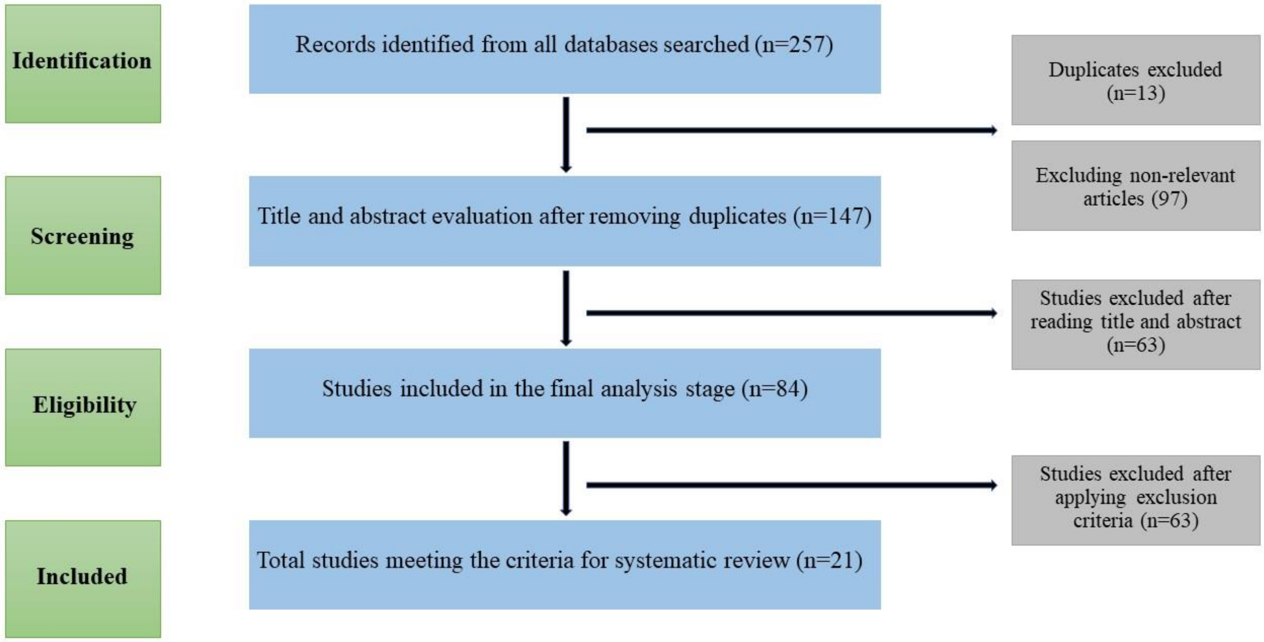

Figure 4. This figure illustrates the current study design and the PRISMA study selection process.

3.1. Pneumonia diagnosis

The results of this systematic review revealed that the predominant focus of applied AI studies in avian radiology has been on industrial poultry, particularly broilers and turkeys. This is mainly due to the high economic need for rapid, automated diagnostic methods in large flocks, as well as the relatively easy access to large volumes of standardized image data in this industry. Pneumonia (especially bacterial pneumonia caused by agents such as *Ornithobacterium rhinotracheales* and *Escherichia coli*) was identified as the most common diagnostic target in this area [33-37]. Deep learning-based algorithms, specifically CNNs such as the ResNet and EfficientNet architectures, have demonstrated their ability to distinguish healthy chest radiographs from those with pneumonia with accuracies often exceeding 95%. These models have generally focused on identifying diffuse opacity patterns in the lung parenchyma and the alveolar region.

3.2. Promising performance in the detection of other diseases and abnormalities

Although the study volume is smaller, there is considerable evidence of AI's potential for detecting a broader range of pathological conditions across different bird species. In domestic and ornamental birds (such as parrots), algorithms for detecting ascites (fluid accumulation in the abdominal cavity), hepatomegaly (enlarged liver), and visceral masses have been tested with initial success [38-40]. Furthermore, in the orthopedic field, AI systems have demonstrated the ability to automatically detect long-bone fractures, joint dislocations, and even metabolic bone abnormalities. An interesting application area is the detection of metallic and non-metallic foreign bodies in gizzards, which could be of immediate clinical value, especially in emergency cases. The reported accuracy in these diverse tasks typically ranges from 85% to 93%.

3.3. Capable of precise anatomical segmentation and quantitative measurement

Beyond qualitative recognition, one of the most powerful applications of AI highlighted in the reviewed studies was the semantic segmentation of specific anatomical structures. Models such as U-Net achieved very accurate performance in separating pixels from the heart, liver, spleen, kidneys, and air sac regions in avian radiographs [41-43]. This capability allows for the quantitative measurement of vital parameters; for example, the automatic calculation of the cardiothoracic ratio, an important indicator of cardiomegaly, or the precise determination of liver volume and dimensions. This objective and repeatable quantification not only provides clinicians with a valuable tool for monitoring subtle changes over time or response to treatment, but can also promote standardization of image interpretation.

3.4. Challenge of species diversity and data limitation

Despite promising results, a comprehensive analysis of the studies revealed a fundamental and common challenge: severe data limitations and issues of generalizability. The vast majority of models developed have been trained on data from a specific species (mainly chickens) and often from a specific center or scanner. When these models are tested on images of other species with different anatomy (such as broad-breasted birds of prey or small ornamental birds) or even images captured with different imaging techniques, a significant drop in performance is observed. This is due to the enormous anatomical, size, and physical variation in the avian world, which makes it very difficult to create a “universal” model. The small size of the training datasets (often less than a few hundred images) also increases the risk of overfitting.

3.5. Gap between testing and real clinical implementation

Another important finding is a significant gap between the ideal testing environment and real clinical conditions. Many studies have used "clean," preselected datasets in which high-quality images and clear diagnostic cases predominate. In practice, however, radiographs obtained in clinics may face challenges such as suboptimal patient positioning, insufficient contrast, image ambiguities, or concomitant diseases that significantly affect algorithm performance [44, 45]. Very few of the identified studies have evaluated the performance of their model in a prospective clinical trial or in a direct comparison with general veterinarians (not just radiologists). This suggests that the technology is still mainly in the proof-of-concept and research phase and is far from being smoothly integrated into the daily workflow of veterinary clinics (Table 1).

Table 1. The gap between testing and real clinical implementation

Aspect	Controlled Research Environment	Real-World Clinical Environment
Data Quality	Curated, high-quality images with clear pathologies.	Variable quality, suboptimal positioning, poor contrast, and artifacts.
Case Complexity	single disease or clear cases.	Co-morbidities, ambiguous findings, and early or subtle disease stages.
Reference Standard	Expert radiologist consensus or necropsy is the gold standard.	Limited access to specialists; diagnosis often based on response to treatment.
Evaluation Metric	High accuracy, sensitivity, and specificity on test sets.	Impact on workflow efficiency, user trust, and final patient outcome.
Target User	Algorithm developers and researchers.	General veterinarians and technicians with varying levels of expertise.

3.6. Future prospect

The present review also identified several emerging trends and promising areas for future research. First, there is a trend towards developing multi-task models that can simultaneously segment multiple organs and screen for multiple diseases. Second, the use of transfer learning and few-shot learning techniques to address data scarcity for rare species is being explored [46, 47]. Third, the application of AI to more advanced imaging, such as CT scanning, has begun to create accurate

3D models of avian anatomy. However, large areas remain underexplored: applications in wildlife birds, diagnosis of degenerative joint diseases, prediction of chronic disease prognosis, and development of ethical and professional standards for the use of this technology in veterinary medicine (Table 2).

Table 2: Emerging trends and areas for further research

Trend / Area	Description	Potential Impact
Multi-Task Models	Single models perform segmentation, classification, and detection simultaneously.	Increases efficiency and provides comprehensive image analysis.
Advanced Imaging (CT)	Application of AI to 3D cross-sectional imaging, like computed tomography.	Enables detailed 3D anatomical modeling and complex disease assessment.
Transfer / Few-Shot Learning	Techniques to train models with limited data from rare or new species.	Solves the data scarcity problem for non-poultry and wildlife species.
Clinical Decision Support	Systems integrating AI findings with other data for actionable recommendations.	Moves beyond detection to aiding in treatment planning and prognosis.
Wildlife & Conservation	Use of AI in imaging for endangered species health monitoring and research.	Expands the field's scope to ecological and conservation medicine.

To overcome these challenges and accelerate the transfer of this technology from the laboratory to the clinic, specific research strategies are proposed. The priority is to create and share standardized multicenter and international databases containing high-quality images of diverse bird species, carefully annotated by multiple experts, and accompanied by clinical and pathological data. Second, future research should move towards developing robust and adaptable algorithms that can overcome differences in species diversity and imaging techniques by leveraging techniques such as strong transfer learning, domain-blind learning, and multitask learning. Third, it is essential to design rigorous and prospective clinical evaluations to measure the performance, efficiency, and ultimately the impact of AI on bird health outcomes and veterinary decision-making in real-world settings. Fourth, research in less-explored areas, such as CT image analysis, multimodal data integration (e.g., image and laboratory data), and interpretive decision support systems, should be encouraged.

At the levels of development and practical implementation, close collaboration among AI engineers, veterinary radiologists, and avian clinicians is an undeniable necessity for the systems to be truly responsive to clinical needs and user-friendly. The development of ethical and professional standards, guidelines, and protocols for the use of AI in veterinary diagnostics, including accountability and transparency in decision-making, should be on the agenda of professional bodies. To foster this interdisciplinary field, it would be very beneficial to establish training programs and specialized courses that explain the basic concepts of AI to veterinary students and professionals, and the principles of avian anatomy and pathology to data scientists.

The future of avian radiology is likely to see a close coexistence and collaboration between radiologists' expert intelligence and AI. AI systems will act as powerful "digital assistants" that reduce the workload of interpreting large volumes of images, provide early warnings of subtle abnormalities, and provide valuable quantitative data. This collaboration could not only improve the level of bird care in the poultry industry, companion animal medicine, and wildlife conservation, but also enable the advancement of epidemiological and physiological research. Realizing this vision requires a sustained commitment to rigorous interdisciplinary research, investment in data infrastructure, and the definition of professional frameworks. The road ahead is challenging but full of opportunities, and navigating it will create a more accurate, efficient, and evidence-based future for the health of all birds.

4. Conclusion

This systematic review, while identifying the significant potential of AI, revealed major obstacles to its maturity and widespread application in avian radiology. A key challenge is the severe shortage of large, diverse, and well-annotated public datasets. Many studies have been conducted on small, private datasets, making direct comparisons of algorithms and the generalizability of findings impossible. The wide anatomical variation among avian species exacerbates the difficulty of generalizing models and highlights the need for intelligent architectures or specific learning approaches. From a methodological perspective, the heterogeneous quality of studies is a limitation; some lack a strong reference standard, appropriate data segmentation, or transparent reporting of performance measures. Furthermore, the gap between the research environment and clinical reality is profound, as most algorithms have been tested under ideal conditions and on clear cases, and their effectiveness in the face of variable image quality and ambiguous diagnoses, as standard in practice, remains unclear. In summary, AI is rapidly advancing in avian radiology and promises to revolutionize the accuracy, efficiency, and standardization of imaging diagnostics by automating routine interpretations, providing objective quantitative measurements, and aiding complex diagnoses. Early evidence is very promising, particularly for diagnosing avian pneumonia and for anatomical segmentation. However, the technology is still in its early stages of maturity, and significant obstacles must be overcome to fully realize its promise, including the lack of diverse data, the difficulty of generalization across species, and the gap between research and clinical application.

Declarations and statements

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Author contribution

Conceptualization: [Z.B.], …; Methodology: [All Authors], …; Formal analysis and investigation: [All Authors], …; Writing - original draft preparation: [S.Gh., L.B., M.H.M.]; Writing - review and editing: [S.Gh., L.B., M.H.M.], …; Funding acquisition: [Self-funding], …; Supervision: [Z.B.]. All authors checked and approved the final version of the manuscript for publication in the present journal.

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The authors declare no conflict of interest.

Ethical approval

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Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declaration of the use of generative AI

Not used for any purposes

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