Review Article

Artificial Intelligence for the Diagnosis of Infectious Diseases in Veterinary Medicine: A One Health Perspective on Multi-Species Biosurveillance

Abzal Kereyev, Birzhan Nurgaliyev, Faruza Zakirova, Albina Darmenova, Dosmukan Gabdullin, Yerbol Sengaliyev*

Institute of Veterinary and Agrotechnology, Zhangir Khan West Kazakhstan Agrarian and Technical University, 090009 Uralsk, Republic of Kazakhstan.

Abstract | Infectious diseases of food-producing animals impose severe economic, welfare, and zoonotic burdens, yet conventional diagnostics remain slow, intermittent, and labor-intensive. Artificial intelligence (AI) now offers rapid, non-invasive, and scalable alternatives, but the evidence is fragmented across species and modalities and has not been synthesized under a One Health lens. This narrative review consolidates recent peer-reviewed studies on AI-based infectious-disease biosurveillance in poultry, cattle, swine, and aquaculture/recirculating aquaculture systems (RAS), and appraises their methods, performance, and translational readiness. Across sectors, deep-learning computer vision, acoustic analytics, motion and physiological sensing via the Internet of Things (IoT), and privacy-preserving federated learning achieved consistently high in-sample performance, frequently 90–99% accuracy, for diseases including coccidiosis, Newcastle disease, avian influenza, lumpy skin disease, anaplasmosis, porcine respiratory disease complex, African swine fever, and a range of bacterial and parasitic fish conditions. However, most models were developed on small, single-site or single-region datasets, lacked external validation, and seldom reported sensitivity, specificity, F1-score, calibration, or area under the curve, raising concerns of performance inflation and uncertain field generalizability. Emerging directions multimodal fusion, edge/TinyML deployment, federated learning, and integration with molecular and genomic data point toward continuous, objective, on-farm decision support. Realizing this potential will require large multicenter datasets, harmonized performance reporting, explainable models, and explicit linkage to formal veterinary and public-health surveillance. Coordinated implementation could strengthen antimicrobial stewardship and zoonotic-risk reduction at the animal–human–environment interface.

Keywords | Artificial intelligence, Biosurveillance, Deep learning, One health, Veterinary diagnostics, Zoonoses

Received | May 02, 2026; **Accepted** | June 15, 2026; **Published** | June 20, 2026
***Correspondence** | Yerbol Sengaliyev, Institute of Veterinary and Agrotechnology, Zhangir Khan West Kazakhstan Agrarian and Technical University, 090009 Uralsk, Republic of Kazakhstan; **Email:** s_erbol89@mail.ru
Citation | Kereyev A, Nurgaliyev B, Zakirova F, Darmenova A, Gabdullin D, Sengaliyev Y (2026). Artificial intelligence for the diagnosis of infectious diseases in veterinary medicine: A one health perspective on multi-species biosurveillance. Adv. Anim. Vet. Sci., 14(6):1302-1311.
DOI | https://dx.doi.org/10.17582/journal.aavs/2026/14.6.1302.1311
ISSN (Online) | 2307-8316

INTRODUCTION

Infectious diseases of food-producing animals remain a primary constraint on global productivity, animal welfare, and public health, with intensification of poultry, cattle, swine, and aquaculture systems amplifying the risk of high-impact and zoonotic pathogens (Degu and Simegn, 2023; Bohara *et al*., 2023). Conventional diagnosis depends on clinical inspection, culture, and laboratory confirmation that are accurate but slow, intermittent, costly, and labor-intensive, and that scale poorly to flock, herd, or pond level (Degu and Simegn, 2023; Lagua *et al*., 2023; Macaulay *et* *al*., 2022). These constraints are most acute in low-resource and high-density production settings, where delayed detection drives antimicrobial overuse, production loss, and onward transmission, including from sectors of direct regional relevance such as South Asian dairy and Pakistani livestock systems (Bhamashetti *et al*., 2025; Arshad *et al*., 2024).

Artificial intelligence (AI), encompassing machine learning (ML) and deep learning (DL), has emerged as a candidate solution by enabling rapid, non-invasive, and continuous detection from images, sounds, motion, and environmental signals (Manikandan and Neethirajan, 2025; Ahmed *et al*., 2021a; Rohini *et al*., 2026). Reported applications already span smartphone-based fecal and lesion imaging, acoustic recognition of disease-specific vocalizations, IoT-linked physiological and motion sensing, and predictive syndromic surveillance from production records (Pranta, 2025; Dhungana *et al*., 2025; Eddicks *et al*., 2024; Blair *et al*., 2022). Yet the literature has accumulated as disconnected, predominantly single-species and single-modality reports, and the dominant theme is phenotypic detection rather than pathogen-level or genomic diagnosis (Nazerke *et al*., 2025).

Despite this rapid growth, no synthesis has integrated AI infectious-disease diagnostics across the major animal-production sectors within a One Health framework, benchmarked their reported performance against one another, or systematically interrogated whether high in-sample accuracy translates into field-deployable, surveillance-grade tools. This gap matters because the value of AI biosurveillance lies precisely in its capacity to link farm-level detection to antimicrobial stewardship and zoonotic-risk reduction across the animal–human–environment interface (Manikandan and Neethirajan, 2025; Nazerke *et al*., 2025). In this review we therefore (i) map current AI methods and their diagnostic performance for infectious diseases in poultry, cattle, swine, and aquaculture/RAS; (ii) critically appraise their methodological quality, external validity, and reporting transparency; and (iii) consolidate cross-sector knowledge gaps into a unified, translation-oriented research and one health agenda. The review is organized by production sector, each supported by an evidence-summary table, followed by an integrated one health analysis, a cross-cutting appraisal of gaps and future perspectives, and conclusions.

Review methodology

This narrative review followed a transparent, reproducible search strategy. We searched PubMed, Scopus, Web of Science Core Collection, CAB Abstracts (CABI Digital Library), IEEE Xplore, and Google Scholar for English-language records published between January 2020 and April 2026, supplemented by hand-searching reference lists and forward-citation tracking. Boolean strings combined controlled and free-text terms across three concept blocks, for example: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "convolutional neural network" OR "computer vision") AND (poultry OR chicken OR cattle OR bovine OR swine OR pig OR fish OR aquaculture OR shrimp) AND (diagnosis OR detection OR surveillance OR "infectious disease" OR zoonos*)). Eligible studies were peer-reviewed primary studies, preprints with full data, and authoritative reviews that reported an AI/ML method applied to the diagnosis or surveillance of an infectious disease in the target species, with at least a qualitative performance descriptor. We excluded opinion pieces, studies addressing only non-infectious conditions, and records without retrievable methods. Screening proceeded by title/abstract followed by full-text assessment; duplicates were removed before screening. The present synthesis is based on the included primary and review studies summarized in Tables 1–4.

Artificial intelligence for poultry infectious disease biosurveillance

Rapid, non-invasive, and scalable diagnostics are central to modern poultry health management because intensification heightens the risk of coccidiosis, salmonellosis, Newcastle disease, and avian influenza, all of which carry major economic and zoonotic relevance (Degu and Simegn, 2023; Pranta, 2025; Dhungana *et al*., 2025). Continuous flock-level monitoring is impractical with manual diagnostics, and AI-driven image, acoustic, and sensor analytics have therefore been positioned as tools that address labor constraints while enabling real-time detection, albeit against persistent concerns of dataset bias, limited multi-farm validation, and uncertain robustness under variable field conditions (Manikandan and Neethirajan, 2025; Ahmed *et al*., 2021a).

For image-based fecal diagnostics, a YOLOV3 with ResNet50 pipeline performed smartphone fecal-image segmentation and four-class disease classification at 98.7% accuracy (Degu and Simegn, 2023), a lightweight MobileNetV2–support vector machine (SVM) pipeline reached 96.17% accuracy with 61 ms inference suited to web and mobile deployment (Pranta, 2025), and an integrated YOLOv11n with EfficientNetB0 system achieved a mean average precision at 0.5 (mAP@0.5) of 0.881 for lesion localization and 99.12% classification accuracy, including perfect precision for underrepresented Newcastle disease (Dhungana *et al*., 2025). For acoustic surveillance, convolutional neural network (CNN) models classified Newcastle disease and avian influenza from vocalizations and spectrograms at 98.5% and 97.5% accuracy, respectively, while broader ML/DL architectures supported

Table 1: Artificial-intelligence methods and reported performance for poultry infectious-disease biosurveillance.

Disease name	AI method	Data type	Key Findings	Best performance	Limitations	Scale	Source
Coccidiosis, Salmonella, Newcastle disease, Healthy	YOLO-V3 + ResNet50 DL	Smartphone fecal images	ROI detection + 4-class classification of fecal images for common enteric/respiratory diseases	mAP (ROI) 87.48%; classification accuracy 98.7%	Single public dataset; no field validation; image quality and farm variability not assessed	Experimental, lab-based	(Degu and Simegn, 2023)
Coccidiosis, Salmonella, Healthy	MobileNetV2 feature extractor + SVM; MobileNetV3Small + ML	Fecal images (web/smartphone)	Lightweight transfer learning for farmer-accessible web diagnostics; real-time inference (61 ms/image)	MobileNetV2–SVM: 96.17% accuracy; 96% precision, recall, F1-score	Single-region data (Tanzania); no explicit farm-level clustering; limited real-world deployment testing	Experimental; web tool prototype	(Pranta, 2025)
Coccidiosis, Newcastle disease, Salmonella, Healthy	YOLOv11n + EfficientNet-B0 DL	PCR-verified fecal images	Integrated detection-classification pipeline; real-time web-based screening for multiple diseases	YOLOv11n: mAP@0.5= 0.881; EfficientNet-B0: 99.12% accuracy; precision for NCD= 1.00	Underrepresentation of NCD; requires field testing, broader regions, more diseases	Experimental; near real-time pipeline	(Dhungana *et al.*, 2025)
Newcastle disease	Deep Poultry Vocalisation Network (CNN-based)	Vocalizations (acoustic)	Disease recognition from calls of infected vs. healthy chickens	Accuracy 98.5%	Task-specific dataset; generalization across farms/breeds not established; interpretability limited	Experimental, lab-scale	(Manikandan and Neethirajan, 2025)
Avian influenza	CNN (CSCNN)	Spectrograms of vocalizations	Classification of AI-infected vs. healthy birds using frequency-filtered, augmented spectrograms	Accuracy 97.5%	Context-specific audio; robustness to complex farm noise untested	Experimental	(Manikandan and Neethirajan, 2025)
Mixed health states (including respiratory problems)	Various ML/DL (CNN, LSTM, self-supervised models such as wav2vec2, Whisper)	Longitudinal vocalizations	AI models detect stress, disease-related acoustic changes over 30–65 days; supports continuous welfare/disease monitoring	Reported "high" performance across tasks; individual metrics vary by model/dataset	Lack of standardized datasets and evaluation protocols; limited cross-farm validations	Multi-study, research synthesis	(Manikandan and Neethirajan, 2025)
Sickness (unspecified diseases) vs. healthy	ML classifiers (with GAN-based data augmentation)	IoT accelerometer/gyro motion data	Industrial IoT predictive service for early detection using motion features and synthetic data	Best model accuracy 97%	Disease not etiologically specified; simulated/augmented data; no pathogen-level diagnosis	Conceptual/experimental farm framework	(Ahmed *et al.*, 2021a)

AI, Artificial intelligence; ML, Machine learning; DL, Deep learning; CNN, Convolutional neural network; SVM, Support vector machine; ROI, Region of interest; mAP, Mean average precision; NCD, Newcastle disease; GAN, Generative adversarial network; IoT, Internet of Things; AUC, Area under the curve.

longitudinal welfare and respiratory-disease monitoring over 30–65 days (Manikandan and Neethirajan, 2025). For motion-based early warning, an Industrial IoT framework combining accelerometer and gyroscope data with generative-adversarial-network–augmented classifiers distinguished sick from healthy birds at 97% accuracy (Ahmed *et al.*, 2021a). Taken together, these studies show that image, acoustic, and IoT modalities each achieve high in-sample performance for major poultry infections (Table 1), yet their reliance on single public datasets and laboratory-like conditions means that comparative field robustness across modalities remains untested and that the choice of modality should currently be driven by deployment context rather than by demonstrated superiority.

Artificial intelligence for cattle infectious disease biosurveillance

Digital and AI-based systems are reshaping cattle health surveillance by enabling earlier, more objective detection of infectious and production-limiting diseases across sensor-based monitoring, image-based diagnosis, and multimodal architectures (Bhamashetti *et al*., 2025; Senthilkumar *et al*., 2024; Arshad *et al*., 2024). These applications directly address productivity loss, welfare compromise, and zoonotic risk, but they share recurrent challenges of limited external validation, farm-to-farm generalizability, data quality, and deployment in resource-constrained settings (Swain *et al*., 2024; Kittichai *et al*., 2025; Paulauskaitė-Tarasevičienė *et al*., 2026).

Sensor-based approaches predicted febrile, metabolic, and infectious conditions using wearable IoT data, with a random-forest architecture reporting up to 93.2% prediction accuracy and a 40% gain in detection efficiency over manual methods (Bhamashetti *et al*., 2025), and a Gaussian Naïve Bayes classifier within a federated-learning framework enabling privacy-preserving, distributed diagnosis of fever, mastitis, foot-and-mouth disease, and ketosis across farm, hospital, and veterinarian datasets (Arshad *et al*., 2024). Symptom-based ML on tabular clinical data likewise favored random forest for general disease prediction (88% accuracy), though without disease-specific metrics (Swain *et al*., 2024). Image-based DL targeted single diseases with very high discrimination: pretrained CNNs detected lumpy skin disease (LSD) with VGG16 and MobileNetV2 reaching 96.07% and 96.39% accuracy (Senthilkumar *et al*., 2024), an ensemble of Vision Transformer and ConvMixer further improved LSD lesion classification (Pal *et al*., 2025), and a deep contrastive-learning image-retrieval system diagnosed *Anaplasma marginale* from blood smears at 91.3% accuracy while reducing observer variability (Kittichai *et al*., 2025). Multimodal fusion of automated milking data, thermal imaging, and intra-ruminal bolus sensing detected udder, leg, and hoof disorders before overt clinical signs at 91.62% accuracy and an area under the curve (AUC) of 0.94 (Paulauskaitė-Tarasevičienė *et al*., 2026). Across these heterogeneous datasets, broad sensor and symptom models offer non-specific early warning while image-based DL offers high single-disease precision (Table 2); because their comparative field performance has not been tested head-to-head and most rest on single-site data, current evidence supports complementary rather than interchangeable deployment.

Artificial intelligence in swine infectious disease biosurveillance

Swine respiratory and systemic viral diseases cause major losses, and because conventional diagnostics are costly, intermittent, and labor-intensive, AI tools must contend with multi-microbial infections, overlapping clinical signs, noisy farm data, and variable infrastructure (Eddicks *et al*., 2024; Lagua *et al*., 2023; Nasim *et al*., 2024). Reported applications cluster around sound-based cough recognition for porcine respiratory disease complex (PRDC), ML-based early-warning models built on production and environmental data, and DL computer vision for African swine fever (ASF) (Bakshi *et al*., 2025; Blair *et al*., 2022; Nazerke *et al*., 2025).

For respiratory surveillance, continuous 24/7 cough monitoring associated high swine influenza A virus loads in oral fluids and aerosols with a decreased AI-derived respiratory-health score, improving etiologic interpretation when combined with quantitative PCR (Eddicks *et al*., 2024), and a body of cough-detection studies using CNNs and SVMs reliably recognized coughing events though with heterogeneous datasets and limited external validation (Lagua *et al*., 2023). For predictive surveillance, supervised ML on farm-level features generated 7- and 30-day infection-probability early warnings across two large commercial systems (Nasim *et al*., 2024), while ML-based syndromic surveillance on sow production records detected porcine reproductive and respiratory syndrome virus introductions one to three weeks earlier than farm reports (Blair *et al*., 2022). For ASF, a YOLO-based classifier of smartphone lateral-flow-assay images improved sensitivity and standardized interpretation, integrating with cloud mapping for real-time geovisualization (86.3% accuracy; 96.3% precision) (Bakshi *et al*., 2025); complementary multi-agent AI frameworks have been proposed to coordinate detection across heterogeneous data streams (Mairittha *et al*., 2025), and broader AI/ML approaches were proposed for genomic, qPCR, and GIS-linked outbreak mapping (Nazerke *et al*., 2025). Collectively, swine studies converge on strong potential for earlier, automated detection (Table 3) most convincingly for ASF rapid-test reading and syndromic PRRSV surveillance but disease-specific quantitative validation is uneven and frequently omits sensitivity, specificity, and calibration, so these tools are best regarded as decision-support augmentations pending multi-farm benchmarking against gold-standard diagnostics.

Artificial intelligence in aquaculture and RAS disease biosurveillance

Aquaculture disease is a leading constraint on productivity and food security, and hidden underwater environments together with limited diagnostic capacity hinder timely detection, motivating a shift from reactive treatment to predictive, real-time biosurveillance in intensive and IoT-enabled systems including recirculating aquaculture systems (RAS) (Bohara *et al*., 2023; Islam *et al*., 2024;

Table 2: Artificial-intelligence methods and reported performance for cattle infectious-disease biosurveillance.

Disease name	AI method	Data type	Key findings	Best performance	Limitations	Scale	Source
Non-specific infectious/ metabolic syndromes (incl. FMD risk)	Random Forest	Wearable IoT sensors (temperature, pulse, motion)	IoT–ML architecture enabled real-time health monitoring and early disease prediction; 40% gain in detection efficiency vs. manual methods	Disease prediction accuracy up to 93.2%; HR 94%, temperature 91%, motion 97%	Limited large-scale validation; challenges with edge intelligence and dynamic model retraining	Experimental, multi-cattle prototype	(Bhamashetti *et al.*, 2025)
Multiple cattle diseases (clinical signs–based)	RF, SVM, Naïve Bayes, IBk, PART	Tabular clinical/symptom data (n=2000)	RF consistently outperformed other ML models for general cattle disease prediction	RF test accuracy 88%	Symptom based dataset; limited external validation; disease specific metrics not reported	Single integrated dataset, experimental	(Swain *et al.*, 2024)
Lumpy skin disease (LSD)	Multiple pre-trained CNNs (VGG16, MobileNetV2, ResNet152V2, etc., transfer learning)	RGB images of healthy, LSD, and other skin diseases	Automated LSD detection with high discriminative performance; robustness improved by including other skin diseases	VGG16: accuracy 96.07%, sensitivity 93.75%, specificity 97.14%; MobileNetV2: accuracy 96.39%, sensitivity 98.57%, specificity 94.59%	Image datasets from limited sources; need field validation and integration into workflows	Image datasets from two public sources	(Senthilkumar *et al.*, 2024)
Lumpy skin disease (LSD)	Vision Transformer, ConvMixer, Ensemble DL model	Lesion images (RGB)	Ensemble of ViT + ConvMixer improved lesion detection and classification; suitable for outbreak management	High precision, recall, F1-score and AUC-ROC (exact values not specified in abstract), ensemble outperformed single models)	Dependent on curated lesion dataset; real-time deployment and broader disease coverage still needed	Public LSD image dataset, experimental	(Pal *et al.*, 2025)
Anaplasmosis (*Anaplasma marginale*)	Deep contrastive learning (ResNeXt-50 backbone + Triplet loss) with kNN image retrieval	Microscopic blood smear images	Automated microscopic diagnosis achieved robust performance and reduced intra-/inter-observer variability)	Baseline: accuracy 91.30%, specificity 92.83%; fine-tuned kNN: accuracy 0.915 ± 0.025, specificity 0.930 ± 0.054, precision 0.833 ± 0.134, recall 0.838 ± 0.118, AUC 0.917–0.922	Data from limited geographic/biological variation; needs larger "open world" datasets for surveillance deployment	Experimental, five-fold cross-validation	(Kittichai *et al.*, 2025)
Udder, leg and hoof infections (grouped as "sick")	Hybrid DL (U-Net, O-Net, ResNet components; multimodal fusion)	Multimodal: automated milking system data, thermal imaging, intra-ruminal bolus sensor	Multimodal AI detected health disorders before overt clinical signs; improved robustness over single-modality models	Overall accuracy 91.62%, AUC 0.94; up to +3% vs. single-modality models	Sample size 88 cows; single commercial farm; grouped "sick" label; requires broader validation and disease-specific stratification	Single commercial farm, cow-day level predictions	(Paulauskaitė *et al.*, 2026)
Fever, mastitis, FMD, ketosis	Gaussian Naïve Bayes within federated learning framework	Wearable body-area sensors (multiple physiological parameters) across three client datasets	Federated learning allowed privacy-preserving, distributed training across farm, hospital and veterinarian data, accurately diagnosing targeted viral/metabolic diseases	Reported "good accuracy" and superiority vs. state-of-the-art; exact metrics not detailed in abstract	Full metrics and per-disease performance not given; early prototype; focused on four diseases	Three-client federated setup (farm, vet hospital, vet)	(Arshad *et al.*, 2024)

AI, Artificial Intelligence; ML, Machine Learning; DL, Deep Learning; RF, Random Forest; SVM, Support Vector Machine; CNN, Convolutional Neural Network; ViT, Vision Transformer; FMD, Foot-and-Mouth Disease; LSD, Lumpy Skin Disease; F1-score, harmonic mean of precision and recall; AUC/AUC-ROC, Area Under the Receiver Operating Characteristic Curve; kNN, k-Nearest Neighbour; IoT, Internet of Things; HR, Heart Rate.

Table 3: Artificial-intelligence methods and reported performance for swine infectious-disease biosurveillance.

Disease name	AI Method	Data Type	Key Findings	Best Performance	Limitations	Scale	Source
PRDC (swIAV, PRRSV, PCV2, others)	Proprietary AI classifier for cough events	Continuous audio + aggregated cough counts; oral fluids, bioaerosols (qPCR)	24/7 cough monitoring associated high swIAV RNA loads in oral fluids/aerosols with decreased AI-derived respiratory health score; improved etiologic interpretation when combined with qPCR	Significant association between high swIAV load and reduced health score; odds of PRRSV/PCV2 detection higher in oral fluids than aerosols	Pathogen-specific performance metrics (Acc/Sens/Spec) not reported; single conventional farm; dependence on algorithm calibration	Single-farm observational deployment	(Eddicks *et al.*, 2024)
PRDC (general respiratory disease)	Various ML/DL cough detectors (e.g. CNNs, SVMs)	Audio (cough sounds) ± temperature/humidity sensors	Reported models reliably recognise coughing events and quantify respiratory burden; commercial AI device adds environmental sensing and alarm thresholds	Individual studies report "good" to "high" cough recognition accuracy; specific pooled metrics not provided	Heterogeneous datasets; noise, overlapping sounds; limited external validation; few disease-specific label sets	Experimental + commercial farm systems (summarised)	(Lagua *et al.*, 2023)
Any infectious disease; PRRSV, PEDV, IAV, M. hyopneumoniae (system 2)	Supervised ML (ensemble-type models)	Farm-level features: farm density, historical test rates, piglet inventory, gestation feed use, wind speed/direction, etc.	Daily infection-probability prediction enabling 7- and 30-day early warning; identifies key risk predictors	Balanced accuracy: "any disease" system ~ high (exact value masked); PRRSV, PEDV, IAV, M. hyo with separate balanced accuracies using six top predictors	Uses proprietary/industry data; model generalisability across regions and pathogens not fully tested; some metrics redacted	Multi-system, multi-farm retrospective study	(Nasim *et al.*, 2024)
PRRSV introduction (sow farms)	ML-based syndromic surveillance on production records	Historical individual sow breeding/farrowing records	ML model predicts expected farrowing outcomes; deviations flag disruptions. Detected PRRSV 1–3 weeks earlier than farm report and earlier than or similar to SPC; also detected non-infectious production disruption	Earlier detection relative to SPC (up to several weeks); sensitivity qualitatively superior in case studies	Only two farms; lacks explicit Acc/Sens/Spec; pathogen non-specific (detects "disruption"); retrospective case-study design	Two commercial sow farms (retrospective)	(Blair *et al.*, 2022)
ASF (field diagnosis via LFA)	YOLO-based deep CNN classifier	Smartphone images of ASF lateral-flow assays	AI enhances reading of LFAs, improving sensitivity and standardising interpretation; integrates with cloud map for real-time geovisualisation of positives	Accuracy 86.3 ± 7.9%; Precision 96.3 ± 2.04%; Recall 79 ± 13.2%; F1-score 0.87 ± 0.088 across splits	Small labelled image dataset; performance may vary with lighting, phone cameras, user technique; comparison with expert readers limited	Prototype; multi-split experimental evaluation	(Bakshi *et al.*, 2025)
ASF (clinical-sign monitoring; cited within	Optical-flow–based motion analysis	Video of pig movement	Reduced activity and decelerated movement used for early ASF detection via computer-vision motion features	Performance metrics not reported in detail in the excerpt	Requires continuous video capture; potential confounders (other illnesses, environment) not fully characterised in excerpt	Experimental video-monitoring study	(Bakshi *et al.*, 2025)
Multiple swine viral infections (ASFV, PRRSV, CSFV, etc.; conceptual/One Health focus)	AI/ML models for genomic and qPCR data; GIS-linked predictive algorithms	Genomic sequences, qPCR outputs, imaging, GIS and IoT-derived data	AI and ML enhance automated interpretation of IFA/microarray/histology images, classification of vaccine vs field strains, and outbreak risk mapping; integration with IoT and GIS supports smart surveillance networks	Individual model metrics not detailed in excerpt; reported as "remarkable precision" and improved interpretive accuracy	Primarily review-level synthesis; limited pig-specific quantitative metrics; implementation barriers include data standards and policy harmonisation	Conceptual and multi-country implementations	(Nazerke *et al.*, 2025)

PRDC, Porcine Respiratory Disease Complex; swIAV, swine influenza A virus; PRRSV, Porcine Reproductive and Respiratory Syndrome Virus; PCV2, Porcine circovirus type 2; PEDV, Porcine Epidemic Diarrhea Virus; IAV, Influenza A virus; M. hyo, Mycoplasma hyopneumoniae; AI, Artificial Intelligence; ML, Machine Learning; DL, Deep Learning; CNN, Convolutional Neural Network; LFA, Lateral Flow Assay; YOLO, You Only Look Once; qPCR, quantitative Polymerase Chain Reaction; GIS, Geographic Information System; SPC, Statistical Process Control; Acc, Accuracy; Sens, Sensitivity; Spec, Specificity.

Table 4: Artificial-intelligence methods and reported performance for aquaculture and RAS disease biosurveillance.

Disease name	AI method	Data type	Key findings	Best performance	Limitations	Scale	Source
Mixed bacterial/parasite skin and fin diseases (visual lesions)	CNNs, SVMs, hybrid DL	Still images, behavior video	Automated recognition of lesions, discoloration, abnormal behavior for rapid diagnosis and monitoring	Reported "quick and precise" detection; models (CNN, SVM) achieve high accuracy on visual symptoms (no explicit % given)	Limited datasets; image variability; not yet validated at farm scale	Conceptual / multi-study synthesis	(Rao, 2025)
Mixed infectious and non-infectious conditions (stress, disease)	DL (CNNs, LSTM, multimodal DL)	Multimodal: water quality, behavior, images	DL-based multimodal HMD captures nonlinear interactions; improves robustness vs handcrafted features	High-performance models reported, but specific accuracy/AUC not detailed	Lack of standardized multimodal datasets; limited generalization to new farms	Review of multiple systems	(Kheriji *et al.*, 2025)
Salmon diseases (various pathogens)	SVM	Lesion images (2D)	Two-stage pipeline (pre-processing + SVM) detects infected salmon under farm-like conditions	Accuracy 91.42% (with augmentation) and 94.12% (without augmentation) in disease classification	Single-species, image-only dataset; no field deployment; recall/precision not reported	Experimental image dataset	(Ahmed *et al.*, 2021a)
Epizootic ulcerative syndrome (Aphanomyces invadans)	Conventional image processing + ML	Lesion images	Automated identification of A. invadans from lesion images in diagnostic workflow	Best method correctly identified A. invadans in 86% of images	Tested on limited dataset; not yet scaled; sensitivity/specificity not separately reported	Prototype / lab-scale	(Macaulay *et al.*, 2022)
Mixed bacterial, viral, parasitic diseases linked to water quality	Random Forest, LSTM	IoT sensor streams (pH, DO, ORP)	Unified AI–IoT buoy platform for disease prediction and water-quality forecasting	RF disease prediction accuracy 98.35%; LSTM time-series forecasting of pH/DO/ORP up to 94% accuracy	Conducted in specific shrimp systems; no external validation; no F1/AUC reported	Pilot deployment	(Rohini *et al.*, 2026)
Visible infectious conditions (skin/fin/gill disease)	Faster R-CNN (X101, R100, R50)	RGB images from fish farms	Faster R-CNN with Detectron2 detects diseased fish in smart IoT context	X101 model reached 98% accuracy on held-out test set	500-image dataset; potential overfitting; no sensitivity/specificity/F1 reported	Small to medium pilot	(Ilyasu *et al.*, 2025)
Multiple infectious diseases and stress-related conditions	AI, ML (various)	Sensors, drones, images, biosensors	Integrates sensors, drones, AI/ML for monitoring water quality, animal health, and behavior	Individual systems report rapid detection; specific metrics generally not provided	Data scarcity, limited reference databases, lack of trained personnel and cost-effectiveness data	Review of technologies	(Bohara *et al.*, 2023)

AI, Artificial Intelligence; ML, Machine Learning; DL, Deep Learning; CNN, Convolutional Neural Network; SVM, Support Vector Machine; LSTM, Long Short-Term Memory network; HMD, Health Monitoring and Diagnosis; IoT, Internet of Things; DO, Dissolved Oxygen; ORP, Oxidation–Reduction Potential; AUC, Area Under the Receiver Operating Characteristic Curve.

Macaulay *et al.*, 2022). Data scarcity, small image libraries, and heterogeneous farm conditions nonetheless limit robust deployment and external validity (Kheriji *et al.*, 2025; Rao, 2025).

Image-based diagnosis used SVMs and CNNs for lesion and behavior recognition, with a two-stage SVM pipeline classifying salmon disease at 91.42–94.12% accuracy (Ahmed *et al.*, 2021b) and a Faster R-CNN model reaching 98% accuracy for visibly diseased farmed fish in a smart-IoT context (Ilyasu *et al.*, 2025), while conventional image processing identified *Aphanomyces invadans*, the agent of epizootic ulcerative syndrome, in 86% of lesion images (Macaulay *et al.*, 2022). Multimodal DL integrating water quality, behavior, and imagery improved robustness over handcrafted features for fish health monitoring and diagnosis (Kheriji *et al.*, 2025), and IoT-linked ML coupled disease prediction with water-quality forecasting, a unified buoy platform reporting 98.35% random-forest disease-prediction accuracy and up to 94% long short-term memory (LSTM) forecasting accuracy for pH, dissolved oxygen, and oxidation–reduction potential (Rohini *et al*., 2026). Broader reviews emphasized the integration of sensors, drones, and AI for monitoring water quality, health, and behavior, but underscored limited reference databases and early-stage validation (Bohara *et al*., 2023; Islam *et al*., 2024). The juxtaposition is instructive: very high accuracies (≥94–98%) reported from small, controlled, often single-species datasets sit in tension with reviews documenting sparse reference data and absent field validation, (Table 4), indicating likely performance inflation and constraining present claims of clinical utility despite genuine promise for proactive, antimicrobial-sparing aquatic health management.

Cross-cutting one health implications

Across all four sectors, the principal One Health value of AI biosurveillance lies in converting earlier, automated detection into reduced antimicrobial use, lower environmental pathogen loads, and decreased cross-species transmission. In poultry, automated recognition of zoonotic pathogens such as *Salmonella* and avian influenza and early detection of flock morbidity can reduce antimicrobial reliance and zoonotic spillover (Degu and Simegn, 2023; Manikandan and Neethirajan, 2025; Dhungana *et al*., 2025). In cattle, earlier detection of foot-and-mouth disease, LSD, and vector-borne anaplasmosis can curtail spread at the livestock wildlife human interface and support outbreak containment and antimicrobial stewardship (Senthilkumar *et al*., 2024; Pal *et al*., 2025; Kittichai *et al*., 2025). In swine, AI-enabled early detection of ASF, PRRSV, and swine influenza in dense production systems lowers zoonotic-spillover and food-security threats through more targeted intervention (Eddicks *et al*., 2024; Nasim *et al*., 2024; Nazerke *et al*., 2025). In aquaculture, improved detection and reduced mortality relieve pressure on wild stocks and mitigate antimicrobial overuse across animal human environment interfaces (Bohara *et al*., 2023; Islam *et al*., 2024; Kheriji *et al*., 2025). Synthesizing these strands, AI diagnostics function as a connective tissue for one health only when farm-level outputs are linked to regional and national surveillance and to zoonotic-risk modeling a linkage that, across the reviewed evidence, remains aspirational rather than operational.

Knowledge gaps and future perspectives

Five cross-cutting limitations recur across sectors and temper the otherwise impressive performance figures. First, apparent accuracy is frequently inflated by evaluation on small, single-site, single-region datasets under laboratory-like conditions, with little external validation, so reported metrics overstate field generalizability (Pranta, 2025; Dhungana *et al*., 2025; Macaulay *et al*., 2022; Ilyasu *et al*., 2025). Second, reporting is heterogeneous and often incomplete: Headline accuracy is common, but sensitivity, specificity, F1-score, AUC, precision, recall, and model calibration are inconsistently disclosed, precluding fair cross-study comparison and clinical risk assessment (Swain *et al*., 2024; Arshad *et al*., 2024; Rohini *et al*., 2026; Ahmed *et al*., 2021b). Third, class imbalance and coarse outcome labels for example underrepresented Newcastle disease or aggregated "sick versus healthy" categories weaken epidemiological inference and disease-specific stratification (Dhungana *et al*., 2025; Paulauskaitė-Tarasevičienė *et al*., 2026). Fourth, the current focus is overwhelmingly phenotypic; genomic, transcriptomic, and other omics-based AI diagnostics are minimally integrated, and explainable AI tailored to veterinary end-users is largely absent, limiting pathogen-level resolution and clinical trust (Nazerke *et al*., 2025; Kittichai *et al*., 2025). Fifth, farm-level AI outputs are rarely connected to formal veterinary and public-health surveillance or to cost-effectiveness evidence, leaving most tools at prototype stage outside operational early-warning systems (Bohara *et al*., 2023; Nasim *et al*., 2024).

Against these gaps, several convergent trends define the field's trajectory. Lightweight, edge-deployable and TinyML models (for example MobileNet-based architectures) are enabling on-farm inference in low-resource settings (Pranta, 2025; Manikandan and Neethirajan, 2025); end-to-end detection-plus-classification pipelines with web and mobile interfaces are maturing (Degu and Simegn, 2023; Dhungana *et al*., 2025); multimodal fusion of imaging, acoustics, physiology, production, and environmental data is improving early-stage sensitivity (Paulauskaitė-Tarasevičienė *et al*., 2026; Kheriji *et al*., 2025); and federated learning is allowing privacy-preserving training across distributed, multi-institutional data (Arshad *et al*., 2024). Future work should therefore prioritize large, standardized, open multicenter and multi-species datasets; harmonized and complete performance reporting including calibration; prospective field trials of IoT–DL and federated frameworks; integration of pathogen-specific, genomic, and omics data with explainable models; and explicit interoperability with WOAH-, WHO-, and FAO-aligned surveillance infrastructures so that validated prototypes mature into trusted, surveillance-grade decision-support tools.

CONCLUSIONS

Artificial intelligence has advanced rapidly toward rapid, non-invasive, and scalable diagnosis of infectious diseases across poultry, cattle, swine, and aquaculture/RAS, with computer vision, acoustic analytics, IoT and motion sensing, and federated learning repeatedly achieving 90–99% in-sample performance for high-impact and zoonotic pathogens. Synthesized across sectors, however, this performance is not yet matched by external validity: most systems were trained and tested on small, single-site datasets, reported metrics incompletely, focused on phenotype rather than pathogen, and remained disconnected from formal surveillance. The decisive constraint on translation is therefore methodological and infrastructural rather than algorithmic. Bridging it will require multicenter validation, transparent and harmonized reporting, explainable and omics-integrated models, and deliberate coupling of farm-level detection to regional and national One Health surveillance. If these conditions are met, AI biosurveillance can credibly augment veterinarians with continuous, objective monitoring that strengthens antimicrobial stewardship and reduces zoonotic risk at the animal–human–environment interface; until then, its high reported accuracies should be interpreted as promising but provisional.

ACKNOWLEDGEMENT

The authors express their gratitude to West Kazakhstan Agrarian and Technical University named after Zhangir Khan for institutional support and assistance in the preparation of this manuscript.

NOVELTY STATEMENT

This is the first review to integrate AI-based infectious-disease diagnostics across poultry, cattle, swine, and aquaculture/RAS within a unified One Health framework. It cross-benchmarks reported performance, exposes recurrent gaps in external validation and metric reporting, and reframes a fragmented, single-species literature into a consolidated, translation-oriented biosurveillance agenda.

AUTHOR'S CONTRIBUTION

Conceptualization, Y.S. and A.K.; methodology, A.K. and Y.S.; investigation, A.K., B.N., F.Z., A.D. and D.G.; data curation, A.K. and B.N.; writing original draft preparation, A.K., F.Z. and A.D.; writing review and editing, A.K., B.N., F.Z., A.D., D.G. and Y.S.; visualization, B.N. and D.G.; supervision, Y.S.; project administration, Y.S.; funding acquisition, Y.S. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Generative AI and AI assisted technology statement

The authors declare that no generative AI and AI assisted technology was used in the creation of this manuscript.

Conflict of interest

The authors have declared no conflict of interest.

REFERENCES

Ahmed G, Malick R, Akhunzada A, Zahid, S., Sagri, M. R., Gani, A. (2021a). An approach towards IoT-based predictive service for early detection of diseases in poultry chickens. Sustainability, 13: 13396. https://doi.org/10.3390/su132313396

Ahmed M, Aurpa T, Azad M (2021b). Fish disease detection using image-based machine learning technique in aquaculture. J. King Saud Univ. Comp. Inf. Sci., 34(8): Part A. https://doi.org/10.1016/j.jksuci.2021.05.003

Arshad J, Irtisam A, Arif T (2024). A federated learning model for intelligent cattle health monitoring system using body area sensors and IoT. Egypt. Inf. J., 27: 100488. https://doi.org/10.1016/j.eij.2024.100488

Bakshi A, Stetson J, Caragea D, Miller, L. C. (2025). Toward a rapid, sensitive, user-friendly, field-deployable artificial intelligence tool for enhancing African swine fever diagnosis and reporting. Am. J. Vet. Res., 86: S27-S37. https://doi.org/10.2460/ajvr.24.10.0305

Bhamashetti A, S.K. Padaganur, N.K.D.N, A. Yaragal and M. Deshmuk (2025). IoT and machine learning-enabled smart cattle health monitoring for early disease detection. Proc 2025 IEEE 6th Global Conference for Advancement in Technology (GCAT), pp: 1-7. https://doi.org/10.1109/GCAT66372.2025.11368529

Blair B, Malladi S, Lowe J (2022). A case study of the application of artificial intelligence to aid in the clinical detection of porcine reproductive and respiratory syndrome virus in sow farms. Int. J. Comp. Appl., 184: 1-8. https://doi.org/10.5120/ijca2022922061

Bohara K, Joshi P, Acharya K, Ramena G (2023). Emerging technologies revolutionising disease diagnosis and monitoring in aquatic animal health. Rev. Aquacult., 16: 836-854. https://doi.org/10.1111/raq.12870

Degu M, Simegn G, 2023. Smartphone based detection and classification of poultry diseases from chicken fecal images using deep learning techniques. Smart Agric. Technol., 4: 100221. https://doi.org/10.1016/j.atech.2023.100221

Dhungana A, Yang X, Paneru B, Dahal, S., Lu, G., Chai, L. (2025). An integrated deep learning approach for poultry disease detection and classification based on analysis of chicken manure images. Agric. Engin., 7: 278. https://doi.org/10.3390/agriengineering7090278

Eddicks M, Feicht F, Beckjunker J, Genzow, M., Alonso, C., Reese, S., Ritzmann, M., Stadler, J. (2024). Monitoring of respiratory disease patterns in a multimicrobially infected pig population using artificial intelligence and aggregate samples. Viruses, 16: 1575. https://doi.org/10.3390/v16101575

Ilyasu U, Sani Z, Suleiman T (2025). Internet of things-based smart fish farming: Application of smart sensors and computer vision to provide real-time monitoring and diagnosis in aquaculture. J. Basics Appl. Sci. Res., 3: 8. https://doi.org/10.4314/jobasr.v3i2.8

Islam S, Ahammad F, Mohammed H (2024). Cutting-edge technologies for detecting and controlling fish diseases: current status, outlook, and challenges. J. World Aquacult. Soc., 55: e13051. https://doi.org/10.1111/jwas.13051

Kheriji L, Kouadri A, Mansouri M (2025). Deep learning-based fish health monitoring and diagnosis: A review. IEEE Access, 13: 181599-181616. https://doi.org/10.1109/ACCESS.2025.3621487

Kittichai V, Kaewthamasorn M, Arnuphaprasert A, Jomtarak, R., Naing, K.M., Tongloy, T., Chuwongin, S., Boonsang, S. (2025). A deep contrastive learning-based image retrieval system for automatic detection of infectious cattle diseases. J. Big Data, 12: 8. https://doi.org/10.1186/s40537-024-01057-7

Lagua E, Mun H, Ampode K, M. B., Chem, V., Kim, Y.H., Yang, C.J. (2023). Artificial intelligence for automatic monitoring of respiratory health conditions in smart swine farming. Animals, 13: 1860. https://doi.org/10.3390/ani13111860

Macaulay S, Ellison A, Kille P, Cable J (2022). Moving towards improved surveillance and earlier diagnosis of aquatic pathogens: from traditional methods to emerging technologies. Rev. Aquacult., 14: 1813-1829. https://doi.org/10.1111/raq.12674

Mairittha T, Sawanglok T, Raden P, Treesuk S (2025). When pigs get sick: multi-agent AI for swine disease detection. arXiv, 2503.15204.

Manikandan V, Neethirajan S (2025). AI-powered vocalization analysis in poultry: Systematic review of health, behavior, and welfare monitoring. Sensors, 25: 4058. https://doi.org/10.3390/s25134058

Nasim M, Ali M, Samsuzzaman, Kabir, M. S. N., Karim, M. R., Ahmed, S., Kyoung, H., Kim, G., Chung, S. O. (2024). Thermal imaging and computer vision technologies for the enhancement of pig husbandry: A review. J. Anim. Sci. Technol., 66: 31-56. https://doi.org/10.5187/jast.2024.e4

Nazerke K, Ruslan, A., Saule, D., Aida, D., Svetlana, V. (2025). Advances and emerging technologies in the diagnosis of viral infections in pigs: progress, challenges, and One Health perspectives. Vet. World, 18: 3788-3805. https://doi.org/10.14202/vetworld.2025.3788-3805

Pal M, Behera, S., Mohapatra, R. K., Branda, F., Mersal, G. A. M., Mishra, S., El-Bahy, S. M., Pattnaik, G., Pattanaik, S., Ali, M. S., Mishra, A., Tuglo, L. S., Youssef, M. (2025). Implementation of a deep learning system for detection and classification of lumpy skin disease in cattle: Enhancing precision and efficiency in veterinary diagnostics. Vet. Med. Sci., 11: e70664.

Paulauskaitė-Tarasevičienė A, Nakrosis, A., Zymantiene, J., Jurenas, V., Vezys, J., Sederevicius, A., Gruzauskas, R., Oberauskas, V., Japertiene, R., Bubulis, A., Kizauskiene, L., Silinskas, I., Zemaitis, J., Ostasevicius, V. (2026). AI-driven multimodal sensing for early detection of health disorders in dairy cows. Animals, 16: 411. https://doi.org/10.3390/ani16030411

Pranta A (2025). Accessible AI-powered poultry disease diagnostics: development, validation, and web deployment of a farmer-friendly MobileNet-based system for coccidiosis and salmonella detection in resource-constrained settings. Poult. Sci., 105: 106338. https://doi.org/10.1016/j.psj.2025.106338

Rao K (2025). Deep learning and AI tools for monitoring and detecting diseases in freshwater fish populations. Int. J. For. Anim. Fish. Res., 9: 2.3. https://doi.org/10.22161/ijfaf.9.2.3

Rohini P., Kanagachidambaresan G. R., Muralidhar M. "IoT-Enabled Real-Time Monitoring and Disease Prediction System for Sustainable Aquaculture," in IEEE Access, 14, pp. 32506-32522, 2026, doi:10.1109/ACCESS.2026.3668762

Senthilkumar C, Sushmitha C, Vadivu G, Neethirajan S (2024). Early detection of lumpy skin disease in cattle using deep learning - a comparative analysis of pretrained models. Vet. Sci., 11: 510. https://doi.org/10.3390/vetsci11100510

Swain S, Pattnayak, B.K., Mohanty, M.N., Jayasingh, S.K., Patra, K.J., Panda, C (2024). Smart livestock management: integrating IoT for cattle health diagnosis and disease prediction through machine learning. Indones. J. Electric. Engin. Comp. Sci., 34: 1192-1203. https://doi.org/10.11591/ijeecs.v34.i2.pp1192-1203