ISSN: 2456-2912
NAAS Rating (2025): 4.61
VET 2025; SP-10(10): 41-45

www.veterinarypaper.com
Received: 06-09-2025
Accepted: 04-10-2025

OV Shinde
Department of Animal Husbandry and Dairy Science, Yashwantrao Chavan Government College of Agriculture, Karad, Satara, Maharashtra, India

SS Sankpal
Department of Animal Husbandry and Dairy Science, College of Agriculture, Mohopre-Achloli, Mahad, Raigad, Maharashtra, India

YB Kandalkar
Department of Animal Husbandry and Dairy Science, Yashwantrao Chavan Government College of Agriculture, Karad, Dist. Satara, Maharashtra, India

TR Bhosale
Department of Animal Husbandry and Dairy Science, Mahatma Phule Krishi Vidyapeeth, Rahuri, Maharashtra, India

SA Khairnar
Department of Animal Husbandry and Dairy Science, RCSM, College of Agriculture, Kolhapur, Maharashtra, India

Corresponding Author:
OV Shinde
Department of Animal Husbandry and Dairy Science, Yashwantrao Chavan Government College of Agriculture, Karad, Satara, Maharashtra, India

Emerging role of artificial intelligence in animal disease surveillance, prediction and diagnosis: A Review

OV Shinde, SS Sankpal, YB Kandalkar, TR Bhosale and SA Khairnar

DOI: https://www.doi.org/10.22271/veterinary.2025.v10.i10Sa.2623

Abstract
Artificial Intelligence (AI) and its subfields Machine Learning (ML), Deep Learning (DL), Computer Vision (CV), and natural language or sound processing are transforming animal health by enabling faster, earlier, and more objective disease prediction and diagnosis. Applications range from sensor- and camera-based early-warning systems in dairy herds to image-based detection of skin and internal lesions, sound analysis for respiratory and behavioural disorders in poultry and swine, and omics-based predictive models for susceptibility and outbreak forecasting. This review summarizes AI methodologies applied in veterinary sciences, key data sources and sensors, notable use-cases (mastitis, lameness, avian influenza, porcine welfare signals, zoonoses), challenges (data quality, bias, interpretability, deployment), and future directions, including federated learning, multimodal integration, and One Health approaches.

Keywords: Explainable AI, Artificial Intelligence, Machine Learning, deep learning, veterinary diagnostics, animal disease prediction, sensors, computer vision, one health, federated learning

1. Introduction
Artificial Intelligence (AI) has emerged as one of the most transformative technologies of the 21st century. First conceptualized by John McCarthy in the 1950s as "the science and engineering of making intelligent machines," AI has evolved dramatically with the advent of deep learning and advanced machine learning algorithms (Kangude & Raut, 2012; Bohr & Memarzadeh, 2020) [1, 2].
In veterinary medicine, AI is increasingly used to process large, diverse data sensor outputs, wearable device data, imaging, genomic data, environmental and climate records to produce earlier disease detection, predict outbreak risk, and manage animal welfare (Ezanno *et al.*, 2020; May, 2022) [3]. In addition, global concerns about zoonotic spillover and food safety further amplify the importance of robust disease surveillance systems (Pillai, Ramkumar & Nanduri, 2022) [5].
India's National Animal Disease Referral Expert System (NADRES), developed by ICAR-NIVEDI, is a case in point: epidemiological data from multiple centres feed into ML/regression models forecasting disease outbreak risk across regions (Kour *et al.*, 2022). Globally, AI tools have been used with high accuracy for example, ML models achieving > 95% sensitivity and specificity in diagnosing canine hypoadrenocorticism (Reagan *et al.*, 2020) [7], and CNNs automating radiographic/ultrasound image interpretation (Krizhevsky *et al.*, 2017; Nakaura *et al.*, 2020) [8, 9].
However, widespread adoption is hampered by lack of standardization; privacy, ethical, and governance issues; explain ability of "black-box" models; technical and infrastructural constraints, especially in developing countries. The literature also points to a need for consensus on data sharing frameworks, interspecies generalizability, and integrating AI within existing veterinary and public health systems. This review aims to comprehensively explore the emerging applications of AI in the surveillance, prediction, and diagnosis of animal diseases. It discusses current progress, methodologies, tools, representative use cases (including zoonotic disease models), practical challenges, and future directions such as federated learning, multimodal data fusion, and One Health integration.

2. Literature Review

2.1 The Challenge of Disease Prediction and Diagnosis

Veterinary disease prediction and diagnosis face several unique constraints: the diversity of species and breeds; differences in physiology; varied farm practices; limited annotated datasets; fragmented health records. Predicting disease onset before clinical signs emerge can greatly reduce economic losses and improve welfare (Magana *et al.*, 2023) [10].

Recent works include comparative studies of ML algorithms on specific diseases: for example bluetongue risk prediction in small ruminants where Random Forest, ANN, and Logistic Regression were compared for variable importance and classification performance (Gouda *et al.*, 2022) [11]. Also, identification of zoonotic pathogen risk factors and outbreak potential using ML/DL models is increasingly common (Pillai *et al.*, 2022) [5].

Knowledge-based reasoning systems (e.g. decision support tools built upon large veterinary knowledge bases) are being developed to complement purely data-driven models, especially where data are sparse or cases are rare.

2.2 Federated Learning, Privacy, and Distributed Models

A growing approach in healthcare and veterinary health is federated learning (FL), where models are trained locally on distributed data sources and only parameter updates (not raw data) are shared. This preserves privacy and can address fragmented data sources. For example, a federated learning model for cattle health monitoring using body area sensors and IoT in three settings (farm, hospital, veterinary clinic) showed good accuracy diagnosing conditions such as fever, mastitis, foot and mouth disease, and ketosis, outperforming some centralized models in generalization performance.

In human medicine, MDPI's "Reviewing Federated Machine Learning and Its Use in Diseases Prediction" highlights how FL has been used for cardiovascular disease, diabetes, and cancer prediction, with benefits in data privacy and overcoming institutional barriers (Moshawrab *et al.*, 2023) [12]. These results are promising analogues for veterinary applications.

2.3 AI in Veterinary Imaging and Radiomics

Deep learning architectures (CNN, ResNet, U-Net), transfer learning, and ensemble methods are widely used for analysing radiographs, ultrasonography, and other imaging modalities. Radiomics (feature extraction from images) is being integrated to strengthen diagnostic reproducibility and to combine imaging with clinical metadata (Bouhali *et al.*, 2022) [13].

For example, systematic reviews of vision-based cattle identification find that DL models (YOLO, Faster-R-CNN, Inception, ResNet) outperform traditional ML (SVM, KNN, ANN) especially when detecting cattle under varying environmental conditions or identifying individual animals via muzzle pattern or coat features (Hossain *et al.*, 2022) [14].

2.4 Sensing, odor detection, non-conventional biomarkers and Wearables

Non-imaging biomarker methods are also developing: VOC analysis via electronic noses (E-noses), biosensors, metabolic profiling. Haselzadeh (2021) [15] reports ≈96% accuracy in distinguishing cattle disease states using odor recognition with E-nose sensors.

Wearable IoT devices for livestock, integrating sensors for temperature, heart-rate, motion, feeding patterns etc., are being explored in "Wearable Internet of Things enabled precision livestock farming" literature. These works stress biocompatibility, precision, and sustainability of devices for smart farms.

2.5 Precision Livestock Farming (PLF), IoT and Smart Systems

IoT, edge computing, cloud platforms, and smart sensor networks integrate to offer real-time monitoring and decision support. A PubMed study "Internet of Things (IoT): Sensors Application in Dairy Cattle Farming" shows how PLF technologies enable better welfare, reproductive performance, health monitoring and feed optimization through sensor + ML integration (Figure 1).

Smart systems like data dashboards, connected wearables, feed analyzers, and herd-level monitoring platforms are becoming more sophisticated. IoT also supports digital twin technologies for livestock environments, enabling simulation and "what-if" analysis.

2.6 Zoonotic Disease Models and One Health

Zoonoses are a major concern: over 70% of emerging infectious diseases originate from animals (Pillai *et al.*, 2022) [5]. AI models are being used to predict zoonotic pathogen emergence, foodborne disease risk, vector-borne transmission, as well as human-animal interface factors (Innovative applications of artificial intelligence in zoonotic disease management, 2023).

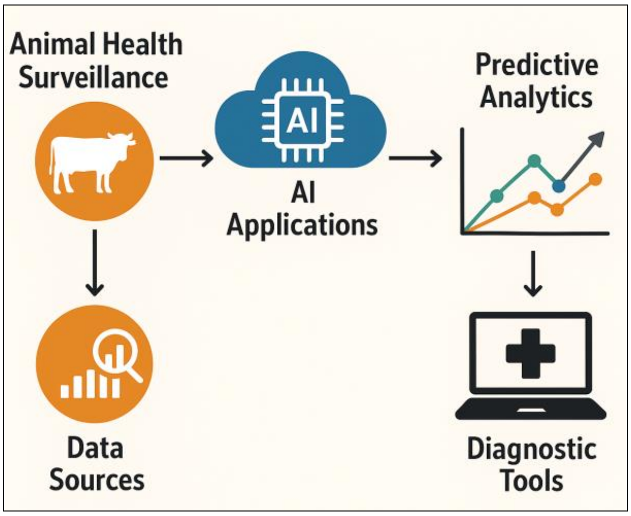

Fig 1: AI-Driven framework for animal disease surveillance and prediction

3. Applications in Livestock Health and Productivity

3.1 Temperature, Physiological and Environmental Monitoring

According to Korelidou (2024) [16] Infrared thermography continues to be utilized for early detection of mastitis, inflammation, or infection via skin temperature gradient studies. Environmental sensors measuring humidity, temperature, ventilation, ammonia levels etc., (Figure 2) are also being fused with animal physiological data to predict respiratory distress or disease risk in housed livestock settings (Gayathri, 2025) [17].

3.2 Reproduction, Estrus, Fertility Prediction

AI models trained on multimodal data motion sensors, feeding behaviour, vocalization, body condition score improve estrus detection. Recent studies also integrate environmental and hormonal data (e.g., progesterone or cortisol levels) to build predictive models of fertility windows, thus improving reproductive efficiency (Verhoeven, 2023) [18].

3.3 Lameness and Gait Disorders
Advances in computer vision and depth cameras make gait analysis increasingly precise detecting stride length, hoof placement, loading patterns. Thermal imaging and pressure mat sensors are now being used together with ML classifiers (e.g. SVM, CNN) to predict early lameness before overt limping occurs (Siachos, 2024) [19].

3.4 Infectious Disease Prediction & Surveillance
Machine learning models have been used for predicting bluetongue risk (small ruminants) (Gouda *et al.,* 2022) [11], also for detection of diseases in calves (e.g. Lumpy Skin Disease) using image or sensor data (AlZubi, 2024) [20]. Outbreak forecasting of avian influenza and porcine welfare signals are in literature too. Early warning systems combining epidemiological, climate, wildlife-spillover, and remote sensing data augmented by AI are showing increasing accuracy for disease emergence.

3.5 Body condition scoring, nutrition and growth monitoring: ML models now use 3D imaging, thermal imaging, weight sensors, feed intake records to automatically score body condition, detect under nutrition or over conditioning. Nutrigenomic models are being introduced linking diet, genetics, micro biome to production outcomes (Semakula, 2021) [21].

3.6 Automation: Robotics, smart devices, vaccination systems
Robotic and automated systems (vaccination, medication dispensing) are being prototyped more often. AI control systems using RFID + vision + robotics enable precise delivery, reducing labour and human error. Also, sensor-driven milking parlours with integrated quality detection are increasingly common (Zhao, 2022) [22].

3.7 Case Study: Federated learning in cattle health monitoring
The federated cattle health monitoring prototype (Egyptian Informatics Journal) used body area sensors and IoT, with Gaussian Naïve Bayes and multiple clients (farm, hospital etc.) as data sources. The federated model was shown to perform well in diagnosis of multiple diseases such as mastitis, ketosis, foot and mouth disease, and fever, with promising generalization across the different client datasets (Arshad, 2024) [23].

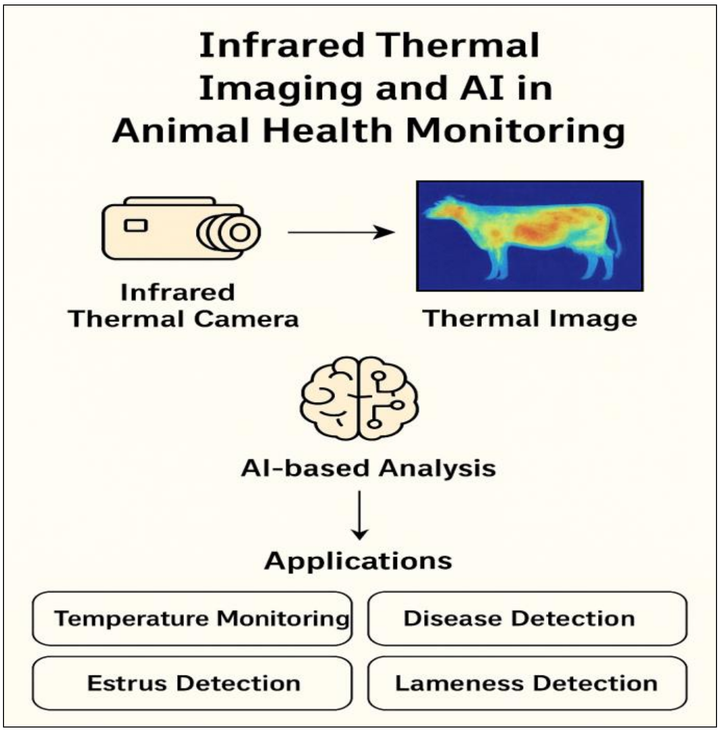

Fig 2: Integration framework of infrared thermal imaging and artificial intelligence for precision livestock health monitoring and management

4. Prospects, Challenges, and Future Directions
4.1 Key Challenges
- **Data Quality & Standardization:** Differences in sensor calibration, imaging protocols, environmental conditions, animal breeds lead to heterogeneous data. Annotated datasets are often small and biased towards certain geographies, species, or production systems (Neethirajan, 2020) [24].
- **Model Interpretability & Explainability:** Black box models (deep neural networks etc.) make veterinary practitioners wary. Explainable AI (XAI) techniques need wider adoption to allow trust and understanding (Aqib, 2023) [25].
- **Privacy, Data Sharing & Governance:** Legal, ethical, and practical barriers limit sharing of data across farms, institutions, and national borders. Federated learning is emerging as a solution but has its own challenges (Rosati, 2025) [26].
- **Infrastructure & Technical Expertise:** Lack of internet connectivity, hardware for processing, and trained personnel in low- and middle-income countries limit adoption (Mollura, 2020) [27].

- **Cost & Economic Viability:** The up-front cost of sensors, robotics, imaging systems, maintenance, training can be prohibitive for smallholders (Pandey, 2025) [28].

4.2 Emerging Trends and Future Research Directions
- **Federated & Meta-Learning Approaches:** To enable privacy-preserving, distributed, multi-institutional model building. Meta-learning may help models adapt to new species or farms with few data points.
- **Multimodal Data Fusion:** Combining imaging, sensor, environmental, genomic, behavioural data to improve predictive accuracy and robustness.
- **Digital Twins and Simulation Models:** Virtual replicas of livestock systems can help run "what-if" scenarios (disease spread, climate change) and optimize interventions. The recent IoT contribution to smart livestock environments highlights digital twin possibilities
- **One Health Integration:** Joint monitoring of animal, human, environmental health; tracking zoonotic transmission; coordinating surveillance across sectors.
- **Sustainability, biocompatibility, ethical device design:** Wearable devices must be animal-friendly; power consumption, materials, maintenance must be sustainable (c.f. W-IoT papers).
- **Explainable & Trustworthy AI:** Techniques like attention maps, feature importance, prototypes, causal modeling to make AI decisions more transparent to veterinarians, animal owners, regulators.

5. Conclusion
AI is already reshaping animal health through predictive, data-driven, and precision-based management. From imaging and sensor networks to federated disease surveillance and smart wearable systems, the technology enhances disease prevention, traceability, welfare, and productivity.

Emerging trends like federated learning, multimodal fusion, digital twins, and One Health integration promise to push the boundaries further, but realization depends on overcoming challenges around data, infrastructure, ethics, and cost.

As the volume, variety, and velocity of animal health data increase, responsibly designed AI tools that are explainable, equitable, and integrated into local contexts will be essential. With interdisciplinary collaboration, standardized protocols, and inclusive deployment strategies, AI can become central to veterinary science and global animal health in the decades ahead.

Conflict of Interest
Not available

Financial Support
Not available

Reference
1. Kangude NA, Raut SB. Introduction to artificial intelligence. Int J Comput Sci Eng Technol; 2012. DOI: 10.1155/2012/145974.
2. Bohr A, Memarzadeh K. The rise of artificial intelligence in healthcare applications. In: Artificial Intelligence in Healthcare. Academic Press; 2020, p. 25-60.
3. Ezanno P, Picault S, Beaunée G, *et al*. Research perspectives on animal health in the era of artificial intelligence. Vet Res. 2021;52:40. DOI: 10.1186/s13567-021-00902.
4. May A, May GS, Müller T, Ertel W. Artificial intelligence as a tool to aid in the differentiation of equine ophthalmic diseases with an emphasis on equine uveitis. Equine Vet J. 2022;54(5):847-855.
5. Pillai N, Ramkumar M, Nanduri B. Artificial intelligence models for zoonotic pathogens: A survey. Microorganisms. 2022;10(10):1911.
6. Kour S, Agrawal R, Sharma N, Tikoo A, Pande N, Sawhney A. Artificial intelligence and its application in animal disease diagnosis. J Anim Res. 2022;12(1):1-10.
7. Reagan KL, Reagan BA, Gilor C. Machine learning algorithm as a diagnostic tool for hypoadrenocorticism in dogs. Domest Anim Endocrinol. 2020;72:106396.
8. Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. Commun ACM. 2017;60(6):84-90.
9. Nakaura T, Higaki T, Awai K, Ikeda O, Yamashita Y. A primer for understanding radiology articles about machine learning and deep learning. Diagn Interv Imaging. 2020;101(12):765-770.
10. Magana J, Gavojdian D, Menahem Y, Lazebnik T, Zamansky A, Progar AA. Machine learning approaches to predict and detect early-onset of digital dermatitis in dairy cows using sensor data. Front Vet Sci. 2023;10:1295430.
11. Gouda W, Sama NU, Al-Waakid G, Humayun M, Jhanjhi NZ. Detection of skin cancer based on skin lesion images using deep learning. Healthcare (Basel). 2022;10(7):1183.
12. Moshawrab M, Adda M, Bouzouane A, Ibrahim H, Raad A. Smart wearable's for the detection of cardiovascular diseases: a systematic literature review. Sensors (Basel). 2023;23(2):828.
13. Bouhali O, Bensmail H, Sheharyar A, David F, Johnson JP. A review of radiomics and artificial intelligence and their application in veterinary diagnostic imaging. Vet Sci. 2022;9(11):620.
14. Hossain ME, Kabir MA, Zheng L, Swain DL, McGrath S, Medway J. A systematic review of machine learning techniques for cattle identification: Datasets, methods and future directions. Artif Intell Agric. 2022;6:138-155.
15. Haselzadeh F. E-noses equipped with artificial intelligence technology for diagnosis of dairy cattle disease in veterinary. KTH Royal Institute of Technology; 2021. URN: URN:NBN:SE:KTH:DIVA-306725.
16. Korelidou V, Simitzis P, Massouras T, Gelasakis AI. Infrared thermography as a diagnostic tool for the assessment of mastitis in dairy ruminants. Animals (Basel). 2024;14(18):2691.
17. Gayathri SL, Bhakat M, Mohanty TK, Kumar RR, Chaturvedi KK, Kumar S. Advanced mastitis detection in Bos indicus cows: a deep learning approach integrated with infrared thermography. J Therm Biol. 2025;104173.
18. Verhoeven S, Chantziaras I, Bernaerdt E, Loicq M, Verhoeven L, Maes D. The evaluation of an artificial intelligence system for estrus detection in sows. Porcine Health Manag. 2023;9(1):9.
19. Siachos N, Neary JM, Smith RF, Oikonomou G. Automated dairy cattle lameness detection utilizing the power of artificial intelligence: Current status quo and future research opportunities. Vet J. 2024;304:106091.
20. AlZubi AA. Convolutional neural network-based approach for classifying Fusarium wilt disease in chickpeas using image analysis. J Anim Plant Sci.

2025;35(1).
21. Semakula J, Corner-Thomas RA, Morris ST, Blair HT, Kenyon PR. Application of machine learning algorithms to predict body condition score from live weight records of mature Romney ewes. Agriculture (Basel). 2021;11(2):162.
22. Zhao Z, Ma Y, Mushtaq A, Rajper AMA, Shehab M, Heybourne A, *et al*. Applications of robotics, artificial intelligence, and digital technologies during COVID-19: a review. Disaster Med Public Health Prep. 2022;16(4):1634-1644.
23. Arshad J, Irtisam A, Arif T, Rasheed MS, Chauhdary ST, Rahmani MKI, *et al*. A federated learning model for intelligent cattle health monitoring system using body area sensors and IoT. Egypt Inform J. 2024;27:100488.
24. Neethirajan S. Transforming the adaptation physiology of farm animals through sensors. Animals (Basel). 2020;10(9):1512.
25. Aqib AI, Fatima M, Muneer A, Atta K, Arslan M, Zaheer CNF, *et al*. Explainable artificial intelligence (XAI) in the veterinary and animal sciences field. In: Explainable Artificial Intelligence for Biomedical Applications. 2023. p. 33-56.
26. Rosati A. Artificial intelligence and the future of animal husbandry: rethinking knowledge, practice, and governance. Arch Latinoam Prod Anim. 2025;33(Suppl 1):567-572.
27. Mollura DJ, Culp MP, Pollack E, Battino G, Scheel JR, Mango VL, *et al*. Artificial intelligence in low- and middle-income countries: Innovating global health radiology. Radiology. 2020;297(3):513-520.
28. Pandey A, Joseph J. Leveraging artificial intelligence for sustainable development in agriculture: an exploratory study. In: Artificial Intelligence and Data Science for Sustainability: Applications and Methods. IGI Global; 2025, p. 187-212.

How to Cite This Article
Shinde OV, Sankpal SS, Kandalkar YB, Bhosale TR, Khairnar SA. Emerging role of artificial intelligence in animal disease surveillance, prediction and diagnosis: A Review. International Journal of Veterinary Sciences and Animal Husbandry. 2025;SP-10(10):41-45.