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Mini Review: Artificial Intelligence in Domestic Animal Reproduction: Current Applications and Future

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Abstract

Advances in digital technologies are rapidly reshaping veterinary medicine, with Artificial Intelligence (AI) emerging as a key tool in improving animal reproductive management. AI enhances breeding efficiency, fertility management, and reproductive health in cattle, pigs, sheep, dogs, and cats. This mini-review explores AI applications, including machine learning (ML), computer vision, and data analytics, which address challenges such as low fertility and genetic selection. Estrus detection leverages AI-powered sensors and vision systems to identify estrus with high accuracy (often >90%) through behavioral and physical indicators, reducing labor costs and missed heats in pigs and cows. Assisted reproductive technologies (ART) also benefit from AI in embryo viability assessment via image analysis, achieving accuracies of up to 79.3% in cattle in vitro fertilization (IVF). In controlled studies, AI sometimes outperforms human evaluators and enhances ultrasound-based pregnancy diagnosis in companion animals. The benefits include improved efficiency, cost reduction, and better welfare through non-invasive monitoring. However, challenges remain, including data privacy, rural accessibility, ethical considerations (such as bias and animal welfare), and the need for large, high-quality datasets. AI holds significant promise for sustainable breeding advancements through big data and hybrid models; nonetheless, integration with veterinary expertise and rigorous validation remains essential.

Keywords: Artificial Intelligence, Domestic Animals, Reproduction, Machine Learning, Estrus Detection

INTRODUCTION

Artificial Intelligence (AI) is transforming veterinary medicine, with key impacts on domestic animal reproduction through ML, computer vision, and data analytics. This addresses challenges like low fertility and genetic selection in species such as cattle, pigs, sheep, dogs, and cats (Kumar et al., 2025).

Recent advancements show AI's role in predictive breeding, with ML handling genomic data for modest gains over traditional methods (Chafai et al., 2023). This covers livestock and emerging companion animal applications, though challenges like data scarcity persist (Dublino and Ercolano, 2025). AI's role is expanding to companion

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animals, aiding in genomic analysis and fertility monitoring, though adoption delays due to data limitations (Akbarein et al., 2025; Akinsulie et al., 2024). These advancements indicate a shift toward data-driven breeding. However, challenges like interpretability and ethical considerations persist. Future research should focus on hybrid AI models, which can further refine genetic selection in domestic animals (Jinya, 2024; Olympica Sarma, 2025).

While AI applications in human reproduction are well-established, their adoption in veterinary reproduction is recent and expanding. The importance of AI in animal reproduction has grown due to increasing demands for sustainable farming, rising companion animals ownership, and the need to minimize issues like climate change impacts on fertility and genetic diversity gaps in breeding programs. This mini-review synthesizes advancements from 2022–2025, focusing on predictive breeding, estrus detection, and ART, while highlighting associated benefits, challenges, and ethical implications. The novelty of this review consists in its cross-species analysis and emphasis on practical integration in both livestock and companion animal contexts.

METHODS

This mini-review synthesizes recent literature on AI applications in domestic animal reproduction. A systematic search was conducted using databases including PubMed, Scopus, Web of Science, and Google Scholar, as well as preprint repositories such as SSRN and Zenodo. Keywords and search terms included combinations of "artificial intelligence," "machine learning," "deep learning," "computer vision," "animal reproduction," "veterinary breeding," "estrus detection," "genomic selection," "assisted reproductive technologies," and species-specific terms like "cattle," "pigs," "sheep," "dogs," and "cats." The search focused on publications from January 2022 to August 2025 to emphasize recent advancements, yielding approximately 100 initial results. Breakdown: PubMed (~30), Scopus (~35), Web of Science (~15), Google Scholar (~10), preprints (~10). After screening for relevance, 34 sources were included.

Inclusion criteria prioritized peer-reviewed articles, comprehensive reviews, and preprints demonstrating empirical or conceptual AI applications in predictive breeding, fertility monitoring, and ART for domestic animals; these were selected for their direct relevance to efficiency gains, challenges, and ethical aspects across species. Exclusions were made for non-English publications, human-focused studies without animal relevance, outdated works predating 2022, and low-quality sources lacking empirical data or rigorous methodology. Although a formal quality assessment (e.g., PRISMA) was not applied due to the narrative mini-review format, the sources were manually evaluated for methodological robustness and for their coverage of benefits, challenges, and ethical considerations to ensure a balanced overview.

KEY APPLICATIONS

Predictive Breeding and Genetic Selection

As introduced earlier, these advancements include AI algorithms that analyze genomic data, pedigree information, and phenotypic traits. They predict breeding outcomes. For instance, in cattle, AI models can predict traits like milk yield or disease resistance. They optimize artificial insemination timing and breeding management (Spangler, 2024). Tools like deep learning networks and ML models have improved accuracy in genomic selection. This is compared to traditional methods such as Genomic Best

Linear Unbiased Prediction (GBLUP). The acquisitions vary by species and trait, e.g., up to 20.8% in pigs for reproduction traits but typically 0.25-3% in recent analyses (Chafai et al., 2023; Su et al., 2025). Variations arise from trait complexity (e.g., polygenic traits benefit more from neural networks than random forests) and dataset size, with larger livestock datasets enabling better performance. In sheep, multiple ML algorithms performed similarly to conventional methods and can predict breeding value (Hamadani et al., 2022). Meanwhile, generative AI addresses data shortage to enhance predictions. However, overfitting leads to poor performance on new, unused data and remains a challenge (Dublino and Ercolano, 2025; Pérez-Enciso et al., 2025). To reduce overfitting, strategies like k-fold cross-validation or regularization are recommended. These advancements promote data-driven selection for superior traits, including productivity and fertility across livestock (Johnsson, 2023; Olympica Sarma, 2025).

For companion animals like dogs and cats, AI applications in predictive breeding are emerging. However, they are less widespread than in livestock. ML models can analyze genomic data, predicting traits related to fertility and health, such as hereditary reproductive disorders. For example, AI has been used in canine breeding, to analyzes genomic databases for predicting litter size and reduces inbreeding risks. It also identifies fertility-related genetic markers. However, studies are limited and require larger datasets for validation (Akinsulie et al., 2024). Similar approaches in cats focus on breed-specific fertility predictions and reduction of pathologies like ovarian cysts.

Overall, while AI applications in predictive breeding and genomic selection show consistently modest improvements in livestock (e.g., cattle and pigs), applications in companion animals are progressing more slowly due to data limitations. This suggests a need for cross-species data sharing and transfer learning (e.g., adapting livestock models to companion animals) to enhance model generalization.

Estrus Detection and Fertility Monitoring

Computer vision and wearable sensors powered by AI detect estrus in animals through behavioral analysis (e.g., via wearable sensors for movement patterns) or computer vision for physical signs. Recent developments in AI-driven estrus detection have incorporated advanced deep learning models. These analyze vulva enlargement in sows. Examples include YOLOv8-based segmentation and key point detection models which measure reproductive organ dimensions with high precision. These achieve 95.2% classification accuracy, 96.0% precision, and 94.5% recall (F1-score ~95%). They use pixel perimeters and Euclidean distances from a single camera setup. This automates monitoring, potentially reducing labor costs by up to 30% while improving optimal breeding timing and litter outcomes (Almadani et al., 2024).

Comprehensive reviews highlight the integration of diverse sensors. These include LiDAR, RFID, and digital infrared thermography. These sensors, combined with ML algorithms, achieve detection rates as high as 97.52% for sound-based estrus identification via convolutional neural networks. They reach up to 98.25% accuracy using deep belief networks for visual behavior analysis. These collectively minimize non-productive days, increase litter size, and generate substantial economic benefits. For example, they provide an estimated €451,000. in additional revenue for large-scale sow operations. This is achieved by optimizing insemination protocols over traditional manual methods (Sharifuzzaman et al., 2024).

In dairy cows, emerging automatic detection technologies fuse AI with heterogeneous data. This comes from activity monitors, infrared thermography, and pressure sensors. They reach efficiencies exceeding 95% through deep learning for behavioral recognition. They reach up to 90.91% in multi-sensor intelligent systems. These facilitate the intelligent evolution of dairy farming and enhance detection rates beyond conventional visual detectors (e.g., tail painting at 98.4%). They address challenges like cost and standardization to support sustainable herd management (Wang et al., 2024).

Additionally, computer vision applications in dairy cattle employ models like YOLOv8 to analyze pose estimation and mounting behavior. These demonstrate promising accuracies over 90% in automated identification and estrus signaling. They enable proactive reproductive interventions and reduce economic losses from suboptimal fertility, in alignment with precision livestock farming mission (Clayton et al., 2024). These innovations underscore the transformative potential of AI in reproductive health monitoring. They prepare the way for increasing data-driven approaches by elevating animal productivity and welfare across diverse livestock systems.

While primarily applied in livestock, similar AI-driven wearable sensors are being adapted for companion animals like dogs, monitoring fertility cycles in a noninvasive way with promising accuracy. In cats, AI apps for home monitoring are in early stages, focused on activity patterns (Akinsulie et al., 2024).

As summarized in Table 1, accuracies in livestock (>90%) exceed those in companion animals (e.g., 76–92% in preliminary studies), likely due to larger datasets and commercial stimulation in livestock; this highlights the potential for transferring livestock models to companion animals with breed-specific adaptations (Akinsulie et al., 2024; MSc et al., 2025).

Assisted Reproductive Technologies (ART)

AI helps in embryo evaluation during in vitro fertilization (IVF) for companion animals and livestock. ML classifies embryo viability from microscopic images. This improves success rates in reproductive technologies like embryo transfer. For instance, in livestock such as cattle, time-lapse monitoring combined with AI-based automated image analysis has shown promise results. It provides accurate, non-invasive embryo assessment. This approach may moderate the intrinsic limitations of traditional morphological evaluation, which have been associated with increased pregnancy failure rates in in vitro–produced (IVP) bovine embryos (Mikkola et al., 2024). Recent advancements include ML models that process embryo data with high precision and outperform human evaluators in routine embryo transfer practices for bovine reproduction (Raes et al., 2025). These AI systems advantage techniques like convolutional neural networks (CNNs). They predict blastocyst development and viability, achieving classification accuracies exceeding 90% in related embryo models (Kim et al., 2024). While some models (e.g., ResNet50) are adapted from human studies, animal-specific validation is essential due to differences in blastocyst morphology. Accuracy metrics such as the Area Under the Receiver Operating Characteristic curve (AUROC), which is 0.741 in humans, may not be directly applicable to animals. Additionally, AI has been applied to oocyte selection in cattle. Deep neural networks and random forest classifiers analyze morphological features of cumulus-oocyte complexes. They outperform expert human assessments and have balanced accuracies up to 79.3% in predicting developmental competence of the blastocyst stage. This approach highlights key predictors such as oocyte size and cumulus density. It offers a standardized, objective method to enhance IVP efficiency in livestock breeding (Raes et al., 2025).

Furthermore, AI integration in IVF laboratories automates embryo selection. It uses deep learning morpho kinetic analysis of time-lapse videos. This reduces subjectivity and increases success rates in predicting viability by using AI-based tools like IVY and ERICA (Hew et al., 2024).

In dogs and cats, emerging AI-driven ultrasound analysis enhances pregnancy diagnosis and anomaly detection. AI applications in imaging include ultrasound and improve diagnostic accuracy for abdominal pathologies. They extend to pregnancy monitoring by recognizing patterns in fetal development and anomalies (Pereira et al., 2023). For example, AI-integrated ultrasound devices are prepared to revolutionize veterinary care and enable faster detection of gestational issues in companion animals. However, further validation is needed for broad implementation. Specific studies on prenatal ultrasound in canines and felines demonstrate its utility. This includes twin diagnosis and fetal assessment. AI potentially facilitates anomaly detection through automated image analysis (Pecchia et al., 2023). Newer AI models, such as CNNs in point-of-care ultrasound (POCUS), have shown promise results. They diagnose pregnancy and uterine infections in small animals like dogs and cats with accuracies exceeding 90% in preliminary trials. They address challenges like operator variability (Burti et al., 2024; Kaffas et al., 2024). AI tools also support broader pregnancy monitoring in dogs and help identify fetal viability and complications in a non-invasive way. Additionally, AI has been applied to semen analysis and artificial insemination in dogs, Table 1. It automates quality assessments to improve fertility outcomes. This extends ART efficiency in companion animals, though data limitations impede progress compared to livestock. Overall, these AI tools boost ART efficiency and also reduce subjectivity in evaluations. They prepare the way for higher reproductive success rates across domestic species (Hew et al., 2024).

Synthesis across ART: Livestock benefits from consolidated image-analysis tools (e.g., CNNs in cattle embryos), while companion animals rely more on ultrasound AI; limitations include cross-species validation, but hybrid approaches could unify these for broader impact. For a comparative overview of accuracies and implications, see Table 1.

Table 1. Different AI approaches, their accuracy, advantages and disadvantages.

Application	Species	AI Method	Accuracy/Improvement	Pros/Cons	Cost Implications	Stage of Development	Reference
Predictive Breeding	Cattle, Pigs	ML, Deep Learning	Modest general gains; up to significant in pigs	Pros: Data-driven selection; Cons: Overfitting risk	Low ongoing; high data setup	Commercial in livestock, experimental in companion animals	(Chafai et al., 2023)
Estrus Detection	Pigs, Cows	Computer Vision (YOLOv8), Sensors	>90%	Pros: Labor reduction; Cons: Sensor costs	30% labor savings	Commercial	(Almadani et al., 2024)
Estrus Detection	Dogs, Cats	Deep Learning (CNNs, e.g., MobileNetV2, ResNet152V2, VGG-16, DenseNet201)	76–92% (approximated range across models in preliminary studies; up to 97.65% with optimized models like Xception)	Pros: Reduces subjectivity, improves consistency; Cons: Requires digitized samples and large training data	Efficiency gains in diagnostics	Experimental	(MSc et al., 2025)
Embryo Viability	Cattle	CNNs, Image Analysis	Up to ~80%	Pros: Outperforms humans; Cons: Needs large images	Efficiency gains	Experimental to commercial	(Raes et al., 2025)
Pregnancy Diagnosis	Dogs, Cats	AI Ultrasound	>90% in trials	Pros: Non-invasive; Cons: Operator variability	Reduced diagnostic costs	Experimental	(Burti et al., 2024)
Semen Analysis	Dogs	ML Automation	Enhanced assessment (e.g., 84–86%)	Pros: Automated; Cons: Dataset needs	Improved fertility outcomes	Experimental	(Hew et al., 2024)

Benefits and Challenges

AI offers significant benefits. These include increased reproductive efficiency, reduced costs, and better animal welfare through non-invasive monitoring. For example, precision farming integrations have boosted herd fertility rates by 10-15% in commercial operations (Akinsulie et al., 2024). AI-powered wearable sensors and monitoring systems enable real-time tracking of livestock health metrics. These include temperature, movement, and reproductive behaviors. They facilitate early detection of issues like estrus or fertility cycles. This optimizes breeding protocols and enhances conception rates. In animal breeding, AI analyzes vast datasets on genetics, physiology, and environmental factors. It predicts optimal insemination timings, identifies prolific animals and reduces inbreeding risks (Akinsulie et al., 2024). Additionally, AI supports disease prediction and early intervention in reproductive pathologies. For example, it detects mastitis or lameness that could impact fertility, which minimizes treatment costs. It promotes sustainable farming practices with lower environmental impact. This includes reducing AI's carbon impact through efficient models. These advancements also contribute to ethical improvements and enable proactive welfare monitoring. For instance, they identify stress or pain through behavioral changes. This stimulates better overall animal health and farm efficiency.

Key challenges include data privacy, scarcity, biases, rural accessibility, and interpretability (see Table 2 for summary). Connectivity issues in remote areas limit real-time AI applications and skills gap among farmers whom needs training for effective use. Furthermore, interoperability between AI systems and existing farm tools can be complex. Model interpretability remains a key issue, like "Black-box" algorithms may obstruct the data value. Biases in datasets (e.g., overrepresentation of certain breeds) could exacerbate inequalities. Validation metrics beyond accuracy are often underreported. These include sensitivity and specificity. This leads to overestimation of performance. Additional challenges: Regulatory gaps (e.g., AI Act implications) and skills gaps requiring farmer training.

Table 2. Benefits and Challenges

Benefits	Challenges
Efficiency ↑ (10-15% fertility boost)	High initial costs
Cost savings (e.g., labor reduction)	Data scarcity & biases
Welfare via non-invasive monitoring	Rural accessibility & connectivity
Ethical proactive health detection	Interpretability & ethical biases
Sustainable practices (lower impact)	Skills gap & interoperability

Ethical Considerations

Ethical issues in AI for domestic animal reproduction include excessive dependence on technology, which may overlook individual animal nuances. They also include the continuation of inequalities through biases in training datasets, such as the underrepresentation of certain breeds or species. Continuous monitoring raises welfare concerns, particularly regarding potential violations of animal autonomy through pervasive surveillance. Furthermore, algorithmic biases may disproportionately impact underrepresented species such as cats, underscoring the necessity for transparent metrics to prevent such risks (Coghlan and Quinn, 2024, 2024). Additionally, the risk of objectifying animals as mere data sources could erode empathetic human-animal bonds crucial for holistic care (Zhang et al., 2024).

In ART contexts, AI applications rise questions about consent, genetic diversity, and long-term health impacts, including higher inbreeding risks or breed-specific vulnerabilities in companion animals (Biasetti et al., 2022). Reproduction-specific dilemmas arise from the overdiagnosis of minor anomalies in embryo selection or oocyte evaluation, potentially leading to unnecessary interventions that compromise welfare. They also include moral challenges in AI-influenced euthanasia for treatable conditions where emotional connections are significant (Raes et al., 2025). Integrated values in large multimodal models may introduce human-centered biases. This can lead to inconsistent evaluations of damage in reproductive contexts and to the overlooking of intensive farming realities (Foris et al., 2025; Kanepajs et al., 2025).

The One Welfare framework highlights interconnected effects on animals, humans, and the environment, calling for consideration of issues like job displacement in farming or environmental costs from AI's computational demands (Foris et al., 2025). Aligning AI with varied ethical perspectives like human and animal welfare focused, or ecosystem centered is essential for equitable animal interests. Reduction strategies involve welfare scientists leading tool validation using models like the Five Domains to emphasize positive states. They also employ blockchain for transparent data handling and promote interdisciplinary collaboration among veterinarians, ethicists, and policymakers to balance innovation with responsibility (Foris et al., 2025).

CONCLUSIONS

The integration of AI in domestic animal reproduction is destinated for growth, driven by developments in big data and edge computing. Key trends include AI's shift from modest predictive gains in livestock to emerging non-invasive tools in companion animals, enhancing overall efficiency and sustainability. Future developments may include AI-optimized cloning or gene editing (supported by ongoing genomic research, e.g., Johnsson, 2023), with expanded applications in companion animals to address fertility problems in aging pet populations. Examples of hybrid models: Combining ML with CRISPR for precise trait editing. However, balanced implementation with veterinary expertise is crucial to navigate ethical and practical challenges. Future research priorities: (1) Building larger companion animal datasets for species-specific models; (2) Developing transparent AI to improve interpretability and trust; (3) Conducting cross-species validations for hybrid approaches. Limitations of this review: Focus on English sources may miss global studies; future work could include multilingual searches. Overall, AI has the potential to revolutionize animal reproduction, but its success depends on rigorous validation, cross-species data integration, and ethical frameworks that prioritize animal welfare and transparency., Figure 1.

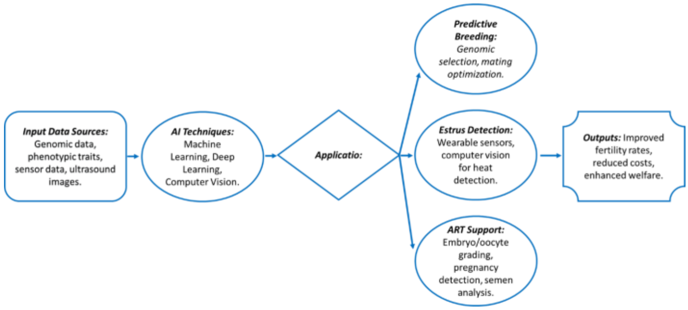

Figure 1. Representative AI workflow illustrating the process from data input through AI analysis to breeding outcomes in domestic animals.

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REFERENCES

1. Akbarein, H., Taaghi, M.H., Mohebbi, M., Soufizadeh, P. (2025) (Applications and Considerations of Artificial Intelligence in Veterinary Sciences: A Narrative Review). Vet. Med. Sci. 11, e70315. https://doi.org/10.1002/vms3.70315
2. Abou Ghayda, R., Cannarella, R., Calogero, A.E., et al. (2023) (Artificial Intelligence in Andrology: From Semen Analysis to Image Diagnostics). World J. Mens Health 41, 39–61. https://doi.org/10.5534/wjmh.230050
3. Akinsulie, O.C., Idris, I., Aliyu, V.A., et al. (2024) (The potential application of artificial intelligence in veterinary clinical practice and biomedical research). Front. Vet. Sci. 11, 1347550. https://doi.org/10.3389/fvets.2024.1347550
4. Almadani, I., Abuhussein, M., Robinson, A.L. (2024) (YOLOv8-Based Estimation of Estrus in Sows Through Reproductive Organ Swelling Analysis Using a Single Camera). Digital 4, 898–913. https://doi.org/10.3390/digital4040044
5. Biasetti, P., Hildebrandt, T.B., Göritz, F., et al. (2022) (Ethical Analysis of the Application of Assisted Reproduction Technologies in Biodiversity Conservation and the Case of White Rhinoceros (Ceratotherium simum) Ovum Pick-Up Procedures). Front. Vet. Sci. 9, 831675. https://doi.org/10.3389/fvets.2022.831675
6. Burti, S., Zotti, A., Banzato, T. (2024) (Artificial intelligence in veterinary diagnostic imaging: Perspectives and limitations). Res. Vet. Sci. 165, 105317. https://doi.org/10.1016/j.rvsc.2024.105317
7. Chafai, N., Hayah, I., Houaga, I., Badaoui, B. (2023) (A review of machine learning models applied to genomic prediction in animal breeding). Front. Genet. 14, 1150596. https://doi.org/10.3389/fgene.2023.1150596
8. Clayton, C., Victory, A., Graves, K., Griffin, A., Hudson, C., McGee, M. (2024) (420 Automated identification and behavioral estrus detection in freestall-housed dairy cows using computer vision and machine learning: A two-layered algorithm approach). J. Anim. Sci. 102, 4–5. https://doi.org/10.1093/jas/skae234.005
9. Coghlan, S., Quinn, T. (2023) (Ethics of using artificial intelligence (AI) in veterinary medicine). AI Soc. 39, 2337–2348. https://doi.org/10.1007/s00146-023-01686-1
10. Dublino, R., Ercolano, M. (2025) (Artificial intelligence redefines agricultural genetics by unlocking the enigma of genomic complexity). Crop J. S2214514125001370. https://doi.org/10.1016/j.cj.2025.05.008
11. El Kaffas, A., Vo-Phamhi, J.M., Kamaya, A., Gevaert, O., Dahl, J.J. (2024) (Critical Advances for Democratizing Ultrasound Diagnostics in Human and Veterinary Medicine). Annu. Rev. Biomed. Eng. 26, 49–65. https://doi.org/10.1146/annurev-bioeng-110222-095229
12. Foris, B., Sheng, K., Dürnberger, C., Oczak, M., Rault, J.-L. (2025) (AI for One Welfare: the role of animal welfare scientists in developing valid and ethical AI-based welfare assessment tools). Front. Vet. Sci. 12, 1645901. https://doi.org/10.3389/fvets.2025.1645901
13. Hamadani, A., Ganai, N.A., Mudasir, S., Shanaz, S., Alam, S., Hussain, I. (2022) (Comparison of artificial intelligence algorithms and their ranking for the prediction of genetic merit in sheep). Sci. Rep. 12, 18726. https://doi.org/10.1038/s41598-022-23499-w
14. Hew, Y., Kutuk, D., Duzcu, T., Ergun, Y., Basar, M. (2024) (Artificial Intelligence in IVF Laboratories: Elevating Outcomes Through Precision and Efficiency). Biology 13, 988. https://doi.org/10.3390/biology13120988
15. Jinya, L. (2024) (Genomic Selection in Livestock Breeding: Advances and Applications). Anim. Mol. Breed. https://doi.org/10.5376/amb.2024.14.0025

16. Johnsson, M. (2023) (Genomics in animal breeding from the perspectives of matrices and molecules). Hereditas 160, 20. https://doi.org/10.1186/s41065-023-00285-w
17. Kalkan, M., Yuksel, B.F., Turanli, M., Uz, M., Kalkan, C. (2025) (Deep Learning–Assisted Vaginal Cytology for Estrus Classification in Dogs and Cats). Authorea Preprints. https://doi.org/10.22541/au.174781114.48367566/v1
18. Kanepajs, A., Basu, A. (2025) (What do Large Language Models Say About Animals? Investigating Risks of Animal Harm in Generated Text). arXiv preprint arXiv:2503.04804. https://doi.org/10.48550/arXiv.2503.04804
19. Kim, H.M., Ko, T., Kang, H., et al. (2024) (Improved prediction of clinical pregnancy using artificial intelligence with enhanced inner cell mass and trophectoderm images). Sci. Rep. 14, 3240. https://doi.org/10.1038/s41598-024-52241-x
20. Kumar, A., Dewry, R.K., Kumar, P., Jasrotia, N., Komal, Singh, K. (2025) (Artificial Intelligence (AI) Significance in The Field of Animal Reproduction). Just Agriculture 5(5), 1-6. e-ISSN: 2582-8223.
21. Menezes, G.L., Mazon, G., Ferreira, R.E.P., Cabrera, V.E., Dorea, J.R.R. (2025) (Artificial intelligence for livestock: a narrative review of the applications of computer vision systems and large language models for animal farming). Anim. Front. 14(6), 42-53. https://doi.org/10.1093/af/vfae048
22. Mikkola, M., Desmet, K.L.J., Kommisrud, E., Riegler, M.A. (2024) (Recent advancements to increase success in assisted reproductive technologies in cattle). Anim. Reprod. 21, e20240031. https://doi.org/10.1590/1984-3143-ar2024-0031
23. Nessler, J.F. (2025) (Editorial: Artificial intelligence in animal behaviour, veterinary behaviour and neurology). Front. Vet. Sci. 12, 1607623. https://doi.org/10.3389/fvets.2025.1607623
24. Olympica Sarma, R.G., S.K. (2025) (Artificial Intelligence in Animal Breeding: A Game Changer). Zenodo (preprint). https://doi.org/10.5281/ZENODO.14829943
25. Pecchia, F., Di Giorgio, S., Sfacteria, A., et al. (2023) (Prenatal Diagnosis of Canine and Feline Twins Using Ultrasound: A Retrospective Study). Animals 13, 3309. https://doi.org/10.3390/ani13213309
26. Pereira, A.I., Franco-Gonçalo, P., Leite, P., et al. (2023) (Artificial Intelligence in Veterinary Imaging: An Overview). Vet. Sci. 10, 320. https://doi.org/10.3390/vetsci10050320
27. Pérez-Enciso, M., Zingaretti, L.M., De Los Campos, G. (2025) (Generative AI for predictive breeding: hopes and caveats). Theor. Appl. Genet. 138, 147. https://doi.org/10.1007/s00122-025-04942-8
28. Raes, A., Babin, D., Pascottini, O.B., et al. (2025) (Artificial intelligence outperforms humans in morphology-based oocyte selection in cattle). Sci. Rep. 15, 21829. https://doi.org/10.1038/s41598-025-09019-6
29. Sharifuzzaman, M., Mun, H.-S., Ampode, K.M.B., et al. (2024) (Technological Tools and Artificial Intelligence in Estrus Detection of Sows—A Comprehensive Review). Animals 14, 471. https://doi.org/10.3390/ani14030471
30. Spangler, M.L. (2024) (461 Machine learning and AI to improve genetic prediction in beef cattle: Potential uses and misuses). J. Anim. Sci. 102, 296–297. https://doi.org/10.1093/jas/skae234.339
31. Su, R., Lv, J., Xue, Y., et al. (2025) (Genomic selection in pig breeding: comparative analysis of machine learning algorithms). Genet. Sel. Evol. 57, 13. https://doi.org/10.1186/s12711-025-00957-3
32. Wang, R., Li, Y., Tian, F., et al. (2024) (Recent Advances in Automatic Estrus Detection Technology for Dairy Cows). SSRN (preprint). https://doi.org/10.2139/ssrn.4996427
33. Xiao, S., Dhand, N.K., Wang, Z., et al. (2025) (Review of applications of deep learning in veterinary diagnostics and animal health). Front. Vet. Sci. 12, 1511522. https://doi.org/10.3389/fvets.2025.1511522
34. Zhang, L., Guo, W., Lv, C., Guo, M., Yang, M., Fu, Q., Liu, X. (2024) (Advancements in artificial intelligence technology for improving animal welfare: Current applications and research progress). Anim. Res. One Health 2, 93–109. https://doi.org/10.1002/aro2.44