

Artificial Intelligence in Veterinary Diagnostics and Healthcare

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Abstract

Artificial intelligence is beginning to influence veterinary diagnostics by assisting with image interpretation, pattern recognition and prediction from large clinical datasets. Algorithms can be trained to evaluate radiographs, ultrasound images, dermatological photographs, pathology slides or retinal images, and to combine laboratory values and patient history into risk estimates. In production animals, AI may also use sensor data to flag animals with abnormal activity, rumination, temperature or milk characteristics. These tools can support faster screening and help prioritise cases, particularly when specialist expertise is limited. However, AI does not remove the need for a veterinary examination. Diagnostic performance depends on the quality and representativeness of training data, and a model may perform differently across species, breeds, equipment or clinical settings. False negative and false positive predictions can both have important consequences. Veterinary AI therefore requires validation, clear reporting of uncertainty and professional oversight. Patient records and images must also be handled with appropriate privacy and cybersecurity safeguards. The most useful role for AI is as decision support: it can draw attention to subtle patterns, reduce repetitive work and improve consistency, while the veterinarian integrates the output with history, physical findings, laboratory results and the owner's circumstances.

Keywords: *Veterinary Diagnostics, Artificial Intelligence, Machine Learning, Imaging, Clinical Decision Support, Digital Health*

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Introduction

Veterinary diagnosis often involves integrating history, examination, laboratory tests and imaging. Artificial intelligence can assist by identifying patterns in data that may be difficult or time-consuming to assess repeatedly. Its role is growing as more veterinary records and images become digital. Practical implementation of introduction should start with a clear baseline and a defined management objective. For safe use of artificial intelligence in veterinary diagnostics and healthcare, priority should be given to using AI to support pattern recognition and prioritisation while keeping clinical responsibility with the veterinarian. A practical plan is to start from a specific diagnostic task, define the intended species and population, and decide how AI

output will be integrated with history, examination and testing. Changes should be introduced consistently so their effects can be interpreted. Workers should know the normal range and the signs that require attention. Monitoring can include turnaround time, agreement with final diagnosis, repeat testing, false positives, false negatives and clinician acceptance. Trends are more useful than isolated readings because season, production stage and local conditions alter expected performance. One limitation is that algorithmic output can be misleading when the patient differs from the data on which the system was trained. Therefore records should be reviewed regularly and important deviations checked by the relevant farm, veterinary, technical or crop specialist. Measures that fit available labour,

infrastructure and budget are more likely to be maintained and to produce reliable long-term benefit.

AI should be understood as a tool that supports, rather than replaces, clinical reasoning. The veterinarian remains responsible for deciding whether a result fits the animal's presentation and whether additional tests or treatment are needed. The value of introduction also depends on integration with the wider production system. Management should connect using AI to support pattern recognition and prioritisation while keeping clinical responsibility with the veterinarian with routine records, clear responsibilities and a response plan. Where equipment, biological processes or field operations are involved, timing, maintenance and quality control matter as much as the initial choice. Records should show what was done and the response observed, particularly for turnaround time, agreement with final diagnosis, repeat testing, false positives, false negatives and clinician acceptance. Evaluation should consider productivity together with health or soil function, labour, input use, risk and economics. Because algorithmic output can be misleading when the patient differs from the data on which the system was trained, weak results should first prompt a review of implementation and local constraints. Comparison with a previous season, baseline or similar group helps separate real improvement from normal variation. This adaptive process allows timing, thresholds and resource use to be refined as experience accumulates.

AI in Diagnostic Imaging

Machine-learning systems can be trained to detect patterns in radiographs, computed tomography, magnetic resonance imaging and ultrasound. Potential applications include screening for fractures, thoracic abnormalities, degenerative joint disease or selected cardiac measurements. Practical implementation of ai in diagnostic imaging should start with a clear baseline and a defined management objective. For safe use of artificial intelligence in veterinary diagnostics and healthcare, priority should be given to supporting review of radiographs, ultrasound, CT, MRI or other images without lowering standards for positioning and image acquisition. A practical

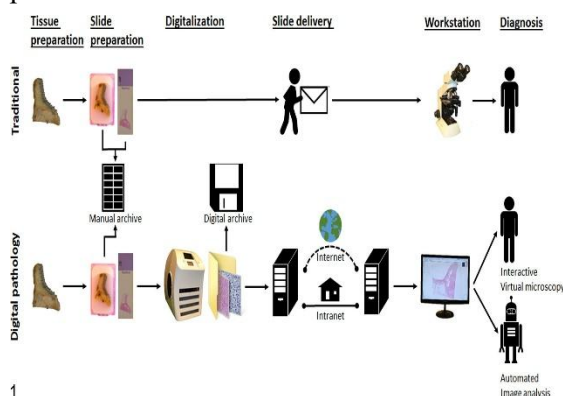
plan is to use validated software, preserve original images, compare predictions with specialist interpretation and audit difficult or discordant cases. Changes should be introduced consistently so their effects can be interpreted. Workers should know the normal range and the signs that require attention. Monitoring can include image quality, sensitivity, specificity, agreement with radiologists, missed lesions, false alerts and reporting time. Trends are more useful than isolated readings because season, production stage and local conditions alter expected performance. One limitation is that poor positioning, artefacts, different machines, species or disease prevalence can reduce performance after deployment. Therefore records should be reviewed regularly and important deviations checked by the relevant farm, veterinary, technical or crop specialist. Measures that fit available labour, infrastructure and budget are more likely to be maintained and to produce reliable long-term benefit.

Image quality and positioning strongly affect performance. A model trained on one machine or species may not generalise to another. AI output should therefore be reviewed alongside the original image, not used as a substitute for image acquisition standards. The value of ai in diagnostic imaging also depends on integration with the wider production system. Management should connect supporting review of radiographs, ultrasound, CT, MRI or other images without lowering standards for positioning and image acquisition with routine records, clear responsibilities and a response plan. Where equipment, biological processes or field operations are involved, timing, maintenance and quality control matter as much as the initial choice. Records should show what was done and the response observed, particularly for image quality, sensitivity, specificity, agreement with radiologists, missed lesions, false alerts and reporting time. Evaluation should consider productivity together with health or soil function, labour, input use, risk and economics. Because poor positioning, artefacts, different machines, species or disease prevalence can reduce performance after deployment, weak results should first prompt a review of implementation and local constraints. Comparison with a previous season, baseline or similar group helps

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Digital Pathology and Cytology

Whole-slide scanners and microscope cameras make it possible to analyse cellular and tissue images computationally. AI can help count cells, identify regions of interest or classify patterns that deserve pathologist review. Practical implementation of digital pathology and cytology should start with a clear baseline and a defined management objective. For safe use of artificial intelligence in veterinary diagnostics and healthcare, priority should be given to assisting cell counting, region-of-interest detection, slide screening and quantitative assessment of tissue or cytological patterns.



A practical plan is to standardise staining, image capture and slide scanning, and ensure pathologists can review the full specimen rather than only algorithm-selected regions. Changes should be introduced consistently so their effects can be interpreted. Workers should know the normal range and the signs that require attention. Monitoring can include scan quality, cell-count agreement, classification accuracy, review time, rejected slides and specialist overrides. Trends are more useful than isolated readings because season, production stage and local conditions alter expected performance. One limitation is that pathology requires clinical and gross context, so image classification alone may miss uncommon or mixed lesions. Therefore records should be reviewed regularly and important deviations checked by the relevant farm, veterinary, technical or crop specialist. Measures that fit available labour,

infrastructure and budget are more likely to be maintained and to produce reliable long-term benefit.

Pathology is complex and often requires context from gross lesions, history and ancillary tests. Algorithms are most valuable for screening and quantification when their limitations are known and when difficult cases are referred for specialist interpretation. The value of digital pathology and cytology also depends on integration with the wider production system. Management should connect assisting cell counting, region-of-interest detection, slide screening and quantitative assessment of tissue or cytological patterns with routine records, clear responsibilities and a response plan. Where equipment, biological processes or field operations are involved, timing, maintenance and quality control matter as much as the initial choice. Records should show what was done and the response observed, particularly for scan quality, cell-count agreement, classification accuracy, review time, rejected slides and specialist overrides. Evaluation should consider productivity together with health or soil function, labour, input use, risk and economics. Because pathology requires clinical and gross context, so image classification alone may miss uncommon or mixed lesions, weak results should first prompt a review of implementation and local constraints. Comparison with a previous season, baseline or similar group helps separate real improvement from normal variation. This adaptive process allows timing, thresholds and resource use to be refined as experience accumulates.

Table 1. Veterinary diagnostic areas where AI can provide decision support.

Area	Potential AI contribution
Radiology	Screen images for selected abnormalities and prioritise cases for review.
Ultrasonography	Support measurement, organ identification or pattern recognition.
Digital pathology	Count cells, highlight regions of interest and assist classification.
Clinical pathology	Combine laboratory values into risk estimates or trend alerts.
Dermatology / ophthalmology	Analyse standardised photographs for screening support.
Remote monitoring	Detect changes in activity, temperature, rumination or other longitudinal signals.

Laboratory Data and Predictive Models

Clinical pathology generates many numerical values that can be combined with age, species and clinical signs. Predictive models may estimate risk of sepsis, renal disease, metabolic disorders or treatment outcome. Practical implementation of laboratory data and predictive models should start with a clear baseline and a defined management objective. For safe use of artificial intelligence in veterinary diagnostics and healthcare, priority should be given to combining haematology, biochemistry, microbiology and history into risk estimates that support but do not replace interpretation. A practical plan is to harmonise units and reference intervals, handle missing values explicitly and validate models against local laboratory methods and case mix. Changes should be introduced consistently so their effects can be interpreted. Workers should know the normal range and the signs that require attention. Monitoring can include calibration, discrimination, false risk categories, missing data, repeat testing and clinical outcome. Trends are more useful than isolated readings because season, production stage and local conditions alter expected performance. One limitation is that reference intervals and disease prevalence vary across species and laboratories, which can shift model performance over time. Therefore records should be reviewed regularly and important deviations checked by the relevant farm, veterinary, technical or crop specialist. Measures that fit available labour, infrastructure and budget are more likely to be maintained and to produce reliable long-term benefit.

Missing data, different laboratory reference intervals and changes in disease prevalence can affect model accuracy. Decision support should show which variables contributed to the prediction and should not hide abnormal values behind a single score. The value of laboratory data and predictive models also depends on integration with the wider production system. Management should connect combining haematology, biochemistry, microbiology and history into risk estimates that support but do not replace interpretation with routine records,

clear responsibilities and a response plan. Where equipment, biological processes or field operations are involved, timing, maintenance and quality control matter as much as the initial choice. Records should show what was done and the response observed, particularly for calibration, discrimination, false risk categories, missing data, repeat testing and clinical outcome. Evaluation should consider productivity together with health or soil function, labour, input use, risk and economics. Because reference intervals and disease prevalence vary across species and laboratories, which can shift model performance over time, weak results should first prompt a review of implementation and local constraints. Comparison with a previous season, baseline or similar group helps separate real improvement from normal variation. This adaptive process allows timing, thresholds and resource use to be refined as experience accumulates.

Wearables and Remote Patient Monitoring

Activity trackers, temperature sensors and other wearable devices can provide longitudinal information between veterinary visits. In livestock, rumination and milk data can help identify animals for examination. In companion animals, home-monitoring devices may support chronic disease follow-up. Practical implementation of wearables and remote patient monitoring should start with a clear baseline and a defined management objective. For safe use of artificial intelligence in veterinary diagnostics and healthcare, priority should be given to tracking activity, temperature, rumination, heart rate or other longitudinal signals between formal examinations. A practical plan is to confirm that devices measure reliably, establish individual baselines and define what change should trigger owner contact or veterinary review. Changes should be introduced consistently so their effects can be interpreted. Workers should know the normal range and the signs that require attention. Monitoring can include wear time, data completeness, alert rate, confirmed deterioration, adherence and recovery trends. Trends are more useful than isolated readings because season, production stage and local conditions alter expected performance. One limitation is that remote signals may indicate

that something has changed without identifying the cause, so examination may still be necessary. Therefore records should be reviewed regularly and important deviations checked by the relevant farm, veterinary, technical or crop specialist. Measures that fit available labour, infrastructure and budget are more likely to be maintained and to produce reliable long-term benefit.

The clinical value comes from change over time. A device should have validated measurement performance, and owners should receive clear instructions about when an alert requires veterinary contact. The value of wearables and remote patient monitoring also depends on integration with the wider production system. Management should connect tracking activity, temperature, rumination, heart rate or other longitudinal signals between formal examinations with routine records, clear responsibilities and a response plan. Where equipment, biological processes or field operations are involved, timing, maintenance and quality control matter as much as the initial choice. Records should show what was done and the response observed, particularly for wear time, data completeness, alert rate, confirmed deterioration, adherence and recovery trends. Evaluation should consider productivity together with health or soil function, labour, input use, risk and economics. Because remote signals may indicate that something has changed without identifying the cause, so examination may still be necessary, weak results should first prompt a review of implementation and local constraints. Comparison with a previous season, baseline or similar group helps separate real improvement from normal variation. This adaptive process allows timing, thresholds and resource use to be refined as experience accumulates.

Telemedicine and Digital Triage

AI-assisted triage tools can organise owner-reported symptoms, photographs or video before a consultation. They may help identify emergencies or route cases to the appropriate service, but remote systems have limited ability to assess pain, hydration, auscultation findings or abdominal abnormalities. Practical implementation of telemedicine and digital triage should start with a clear baseline and a defined management objective. For safe use of

artificial intelligence in veterinary diagnostics and healthcare, priority should be given to organising owner-reported signs, photographs, video and history so urgent cases are prioritised and appropriate follow-up is arranged. A practical plan is to use structured questions, verify identity and location, document limitations and define clear thresholds for in-person examination or emergency referral. Changes should be introduced consistently so their effects can be interpreted. Workers should know the normal range and the signs that require attention. Monitoring can include triage agreement, referral rate, missed urgent cases, consultation time, owner understanding and follow-up completion. Trends are more useful than isolated readings because season, production stage and local conditions alter expected performance. One limitation is that remote assessment is limited when palpation, auscultation, laboratory sampling or imaging is required. Therefore records should be reviewed regularly and important deviations checked by the relevant farm, veterinary, technical or crop specialist. Measures that fit available labour, infrastructure and budget are more likely to be maintained and to produce reliable long-term benefit.

Telemedicine works best for follow-up and situations where a veterinarian can decide whether in-person examination is required. Automated advice should not encourage treatment without adequate diagnosis. The value of telemedicine and digital triage also depends on integration with the wider production system. Management should connect organising owner-reported signs, photographs, video and history so urgent cases are prioritised and appropriate follow-up is arranged with routine records, clear responsibilities and a response plan. Where equipment, biological processes or field operations are involved, timing, maintenance and quality control matter as much as the initial choice. Records should show what was done and the response observed, particularly for triage agreement, referral rate, missed urgent cases, consultation time, owner understanding and follow-up completion. Evaluation should consider productivity together with health or soil function, labour, input use, risk and economics. Because remote assessment is limited when palpation, auscultation,

laboratory sampling or imaging is required, weak results should first prompt a review of implementation and local constraints. Comparison with a previous season, baseline or similar group helps separate real improvement from normal variation. This adaptive process allows timing, thresholds and resource use to be refined as experience accumulates.

Table 2. Safe workflow for AI-assisted veterinary diagnosis.

Step	Recommended practice
Acquire quality data	Use correct imaging, sampling and patient identification procedures.
Run validated tool	Use systems intended for the relevant species and clinical setting.
Review original data	Do not accept an AI label without examining the image, result or patient context.
Compare with clinical findings	Reconcile AI output with history and physical examination.
Resolve disagreement	Seek additional tests or specialist review when findings conflict.
Document decision	Record clinically important AI input and final professional interpretation.

Validation, Bias and Explainability

Veterinary datasets are often smaller and more diverse than human medical datasets. Breed, species, age and referral patterns can create bias. A model that performs well in a specialist hospital may not work equally well in primary care. Practical implementation of validation, bias and explainability should start with a clear baseline and a defined management objective. For safe use of artificial intelligence in veterinary diagnostics and healthcare, priority should be given to ensuring performance is tested in the species, breeds, ages and clinical settings where the tool will actually be used. A practical plan is to conduct external validation, monitor drift after software updates and provide clinicians with understandable reasons or confidence information where possible. Changes should be introduced consistently so their effects can be interpreted. Workers should know the normal range and the signs that require attention. Monitoring can include performance by subgroup, calibration, model drift, override frequency, explanation usefulness and error analysis. Trends are more useful than isolated readings because season, production stage and local conditions alter expected performance. One limitation is that high average accuracy can hide poor performance in rare species, minority breeds or uncommon conditions. Therefore

records should be reviewed regularly and important deviations checked by the relevant farm, veterinary, technical or crop specialist. Measures that fit available labour, infrastructure and budget are more likely to be maintained and to produce reliable long-term benefit.

Independent validation is therefore necessary. Clinicians should know the intended population, performance measures and main failure modes. Explainable outputs improve the ability to detect obviously inappropriate predictions. The value of validation, bias and explainability also depends on integration with the wider production system. Management should connect ensuring performance is tested in the species, breeds, ages and clinical settings where the tool will actually be used with routine records, clear responsibilities and a response plan. Where equipment, biological processes or field operations are involved, timing, maintenance and quality control matter as much as the initial choice. Records should show what was done and the response observed, particularly for performance by subgroup, calibration, model drift, override frequency, explanation usefulness and error analysis. Evaluation should consider productivity together with health or soil function, labour, input use, risk and economics. Because high average accuracy can hide poor performance in rare species, minority breeds or uncommon conditions, weak results should first prompt a review of implementation and local constraints. Comparison with a previous season, baseline or similar group helps separate real improvement from normal variation. This adaptive process allows timing, thresholds and resource use to be refined as experience accumulates.

Ethics, Privacy and Professional Responsibility

Images and clinical records contain sensitive owner and business information. Cloud-based AI services should use appropriate access controls, retention policies and cybersecurity. Clinics should understand whether data are used for secondary model training. Practical implementation of ethics, privacy and professional responsibility should start with a clear baseline and a defined management objective. For safe use of artificial

intelligence in veterinary diagnostics and healthcare, priority should be given to protecting owner information, animal records and clinical accountability when data are stored or processed digitally. A practical plan is to use appropriate consent, secure access, audit trails and clear contracts for cloud services, and document when AI materially affects a decision. Changes should be introduced consistently so their effects can be interpreted. Workers should know the normal range and the signs that require attention. Monitoring can include privacy incidents, access logs, cybersecurity events, documented overrides, complaint resolution and adherence to professional standards. Trends are more useful than isolated readings because season, production stage and local conditions alter expected performance. One limitation is that responsibility cannot be transferred to software; the veterinarian must remain able to question recommendations and justify the final clinical plan. Therefore records should be reviewed regularly and important deviations checked by the relevant farm, veterinary, technical or crop specialist. Measures that fit available labour, infrastructure and budget are more likely to be maintained and to produce reliable long-term benefit.

Professional responsibility remains with the veterinarian. AI recommendations should be documented where they materially influence care, and owners should receive clear explanations when uncertainty affects diagnostic or treatment choices. The value of ethics, privacy and professional responsibility also depends on integration with the wider production system. Management should connect protecting owner information, animal records and clinical accountability when data are stored or processed digitally with routine records, clear responsibilities and a response plan. Where equipment, biological processes or field operations are involved, timing, maintenance and quality control matter as much as the initial choice. Records should show what was done and the response observed, particularly for privacy incidents, access logs, cybersecurity events, documented overrides, complaint resolution and adherence to professional standards. Evaluation should consider productivity together with health or soil function, labour, input use, risk and

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Conclusion

Artificial intelligence has substantial potential in veterinary imaging, pathology, laboratory interpretation and remote monitoring. Its strongest contribution is likely to be faster screening and more consistent decision support.

Safe adoption requires local validation, high-quality data and clear human oversight. Veterinary medicine benefits when AI expands the clinician's ability to recognise patterns while preserving the judgement, communication and accountability that define professional care.

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