Clinical Artificial Intelligence and Machine Learning Metrics 101

How to Evaluate Artificial Intelligence Tools for Veterinary Clinical Practices

Brian Hur, DVM, PhD[a,b,*], Aparna Elangovan, PhD[c], Laura Hardefeldt, BScBVMS, MPH, PhD[b]

KEYWORDS

• Artificial intelligence • Machine learning • Veterinary medicine
• Performance metrics • Model validation • External validation • Diagnostic AI
• Clinical decision support

KEY POINTS

- Evaluating artificial intelligence (AI) tools requires understanding core performance metrics and recognizing that reported performance depends heavily on the population tested.
- AI performance is fundamentally limited by interannotator agreement among expert labelers, a concept often overlooked in validation studies that establishes the ceiling for model evaluation.
- External validation on independent datasets is essential, as AI tools frequently show degraded performance when deployed outside their original training environment due to domain shift.
- In the absence of regulatory oversight for veterinary AI, clinicians bear responsibility for critically evaluating tools before adoption using standardized evaluation frameworks.

INTRODUCTION

The adoption of artificial intelligence (AI) and machine learning (ML) in veterinary medicine has accelerated markedly over the past several years with tools now deployed across diverse clinical applications.[1–3] These range from ambient scribes that automate medical record generation, to computer vision systems that analyze radiographs

[a] Veterinary Information Network, 777 W. Covell, Davis, CA, USA; [b] Department of Veterinary Biosciences, Melbourne Veterinary School, University of Melbourne, Melbourne, Victoria, Australia; [c] Palo Alto, CA, USA
* Corresponding author. Veterinary Information Network, Davis, CA.
E-mail address: brian.hur@vin.com

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Abbreviations	
AI	artificial intelligence
AUC	area under the curve
AUC-ROC	area under the receiver operating characteristic curve
IAA	interannotator agreement
LLM	large language model
ML	machine learning
NPV	negative predictive value
PPV	positive predictive value
PR	precision-recall
ROC	receiver operating characteristic

and pathology slides, to natural language processing pipelines that extract structured data from millions of consultation records.[4–7] The pace of development shows no signs of slowing; if anything, the barrier to creating such tools continues to fall as the same AI technologies powering clinical applications can now assist in their own development.[8]

This lowered barrier to entry for AI development is simultaneously empowering and perilous.[9] In the same way we pay special attention to evaluating other novel therapies in the veterinary profession, we need to also understand how to evaluate AI- and ML-based tools. There are differences in evaluations that should be understood when applying or building such tools.[10] In the early days, developing tools required the ability to code and a deep understanding of ML; however, the same underlying models powering the AI can now help develop the very systems that use AI. This could allow for the proliferation of tools by creators with little or no prior coding experience.[11,12] While these AI and ML tools can be useful, their value can also be overstated, and may in fact be harmful if not evaluated properly. It is imperative that all those engaged in their use understand the mechanisms used for evaluation.[13,14]

The veterinary landscape is unique in many ways which creates challenges when evaluating AI tools.[1,15] Species variation, building AI tools with limited test data compared to human medicine, and diverse practice settings (small animal, large animal, exotic, and emergency) all present significant issues.[16] Furthermore, the field is often less regulated than human medicine and in many regions there are no governing boards to control how individual veterinarians use AI tools.[17,18] An AI tool that might be evaluated in one setting, such as a university teaching hospital, could have a drastically decreased performance when tested in another, such as a general practice clinic, due to their many differences in environments and workflows, which is often referred to as domain shift.[19,20] This was notably demonstrated by a widely deployed sepsis prediction algorithm in human medicine which, on independent external validation, exhibited substantially degraded performance compared to developer-reported metrics while missing the majority of actual sepsis cases.[21]

The veterinary community stands to benefit from the use of AI tools in clinics through improving communication time with patients, simplifying note taking, and reducing the risk of burnout in practitioners.[22–24] Additionally, it can expand research capability through allowing population-based studies rather than relying on manual evaluation of relatively small numbers of clinical records.[25] It also has the potential to evaluate longitudinal records to better understand how treatments can impact patient outcomes.[26]

The purpose of this article is to provide a practical framework for evaluating AI and ML tools in veterinary medicine, applicable both to clinicians assessing

commercial products for adoption and to those developing novel applications. The aim is to equip veterinary professionals, regardless of technical background, with the conceptual foundations and practical heuristics necessary for informed decision making. The framework addresses evaluation across the major AI modalities currently deployed in veterinary practice: documentation and scribe tools, diagnostic imaging, pathology and cytology, dental radiography, and cardiology applications. Throughout, we emphasize that evaluation is not a one-time event but an ongoing process extending from initial assessment through real-world deployment and monitoring.

BACKGROUND

Veterinary medicine presents distinct context for AI development with 3 fundamental challenges: biological heterogeneity across species and breeds, data scarcity and quality issues, and an absence of regulatory oversight. We address each in turn.

Species and Breed Challenges

There are anatomic and physiologic diversity among species, breeds, and individual patients.[27,28] Detecting cardiomegaly on canine thoracic radiographs requires accounting for chest conformation, with the barrel-chested Bulldog, the deep narrow Greyhound thorax, and the keel-shaped Great Dane chest each representing different normal anatomy. A model claiming to *detect heart disease* must specify its target population—all dogs versus specific breeds versus cats. This challenge compounds across species. AI systems trained on canine data cannot transfer directly to felines, even for the same disease.[29] The radiographic appearance of pneumonia differs fundamentally between dogs, cats, and horses. Each species effectively constitutes a separate domain requiring dedicated validation.

Limited Data

Human medical AI benefits from decades of incentivized digitization through meaningful use mandates and standardized coding systems.[30] Veterinary medicine lacks equivalent infrastructure, resulting in a *low-resource* data environment of unstructured free text.[31] A diagnosis of pyoderma might exist as a sentence fragment, *skin looks red, susp pyoderma, dispensing ceph* rather than a coded entry. When AI was used on 4.4 million companion animal records, complete extraction of drug dose, duration, and diagnosis was achievable for only 39% of canine and 37% of feline records.[27] This reflects documentation reality, not algorithmic failure, with direct implications for any AI trained on such data.

However, the veterinary field does benefit from some data advantages. Large-scale clinical databases such as VetCompass (UK and Australia),[32] SAVSNET,[33] and the Dog Aging Project[34] grant researchers access to millions of deidentified clinical records for population-based studies. Unlike human medicine, which is governed by strict regulations in the United States (eg, Health Insurance Portability and Accountability Act), veterinary records face relatively minimal legal regulation regarding research access, potentially improving data availability for AI development.[35] These resources enable epidemiologic research at a scale that would be considerably more difficult to achieve in human medicine due to privacy and regulatory constraints. In addition, growing interest in *big data* for veterinary research is resulting in increasing annotated data sets.

Diverse Practice Settings

Veterinary medicine encompasses fundamentally different environments. For example, a high-volume vaccine clinic that uses checkboxes for its examination records, a general practice with abbreviated documentation, a specialty referral with complex cases and detailed records, or emergency care with time pressured notes which may contain incomplete histories. Furthermore, it could be an exotic species or infrequently used medicine. An AI tool validated in referral hospitals may perform poorly in general practice.[19] This is not because of a flawed system, but because population, documentation style, and clinical context differ substantially.

Regulatory Gaps

The United Stated Food and Drug Administration (FDA) regulates human AI medical devices, requiring safety and efficacy demonstration before market release.[36] No equivalent exists for veterinary AI. Products can reach market without having any oversight beyond what is done by the developer of such products.[17] This means that there are no mandated validation standards, no required transparency about training data, and shifted evaluation burden to individual veterinarians.

The Domain Transfer Problem

These factors converge in domain shift: models trained in one context fail to generalize to another.[37,38] Standard evaluations use hold-out sets from training data, demonstrating only internal validity, that the model learned patterns in that specific dataset. External validity, measured by performance on genuinely independent data, requires separate assessment. For example, a model trained on university hospital data might learn that *lymphadenopathy predicts lymphoma*, because in referral populations it often does. Deployed in primary care, where lymphadenopathy commonly reflects dental infection or reactive inflammation, the model will systematically overpredict neoplasia. The learned correlation was domain specific, not medically universal.[39] Beyond population-level shifts, models may also learn nonclinical artifacts in training data. An AI model might, for instance, base diagnostic predictions partly on documentation style or service-specific phrasing rather than clinical content, learning to associate linguistic patterns with writing styles rather than with underlying pathology.

UNDERSTANDING ARTIFICIAL INTELLIGENCE PERFORMANCE METRICS

Evaluating AI tools requires navigating 2 metric traditions that use different terminology and emphasize different aspects of performance. The AI/ML community typically reports precision, recall, and F1 score. Alternatively, clinical literature favors sensitivity, specificity, and predictive values. These frameworks overlap but are not equivalent, and understanding both is necessary when assessing tools that may report either. Rigorous evaluation requires understanding the metrics used to characterize AI performance.

The Confusion Matrix: Foundation of all Classification Metrics

All classification metrics derive from the confusion matrix, the same framework used for evaluating any diagnostic test, which categorizes predictions into 4 outcomes (**Table 1**)[40]:

A *true positive* occurs when the AI correctly identifies a condition that is present. A *false positive* (type I error) occurs when the AI incorrectly flags a condition that is absent. A *false negative* (type II error) occurs when the AI fails to identify a condition that is present. A *true negative* occurs when the AI correctly identifies absence of a condition.

Table 1
Confusion matrix diagram

	Condition Present	Condition Absent
AI Positive (Test Positive)	**True Positive** (TP)	**False Positive** (FP)
AI Negative (Test Negative)	**False Negative** (FN)	**True Negative** (TN)

Veterinarians routinely apply this reasoning when interpreting laboratory results or imaging findings. AI evaluation requires the same logic, applied with equal rigor. The clinical consequences of these errors differ dramatically by context.[40] For example, consider if an AI system is being relied on for diagnosis of a disease such as osteosarcoma. A false negative for osteosarcoma delays diagnosis of a life-threatening condition. A false positive for the same condition may precipitate unnecessary treatment or even euthanasia. Evaluation must consider not just error rates but error consequences.

The Machine Learning Framework: Precision and Recall

ML research conventionally reports precision and recall, typically combined into an F1 score.[41]

Recall (equivalent to sensitivity) answers: of all positive cases, what proportion did the system identify?

$$Recall = \frac{TP}{TP + FN}$$

Precision (equivalent to positive predictive value) answers: of all cases the system flagged as positive, what proportion was correct?

$$Precision = \frac{TP}{TP + FP}$$

The F1 score is the harmonic mean (a type of average that penalizes extreme imbalance between 2 values) of precision and recall:

$$F1 = \frac{2 \times (P \times R)}{P + R}$$

This framework emphasizes positive class performance, appropriate for ML tasks where the negative class is large, heterogeneous, or not well defined.[41] True negatives do not appear in precision or recall calculations. When evaluating an information extraction system that identifies drug mentions in clinical notes, for instance the universe of *nondrug mentions* is not well defined, making specificity calculations problematic. Precision and recall avoid this issue by focusing exclusively on positive predictions and positive cases.

The Clinical Framework: Sensitivity and Specificity

Clinical medicine conventionally reports sensitivity and specificity, which treat both classes symmetrically.[42]

Sensitivity (also called recall or true positive rate): of all cases with the condition, what proportion did the system correctly identify as positive?

$$Sensitivity = \frac{TP}{TP + FN}$$

High sensitivity means few missed cases, critical for screening applications where failing to detect disease is unacceptable. A pneumonia detection AI with 95% sensitivity misses 5% of pneumonia cases.

Specificity: of all cases without the condition, what proportion did the system correctly identify as negative?

$$Specificity = \frac{TN}{TN + FP}$$

High specificity means few false alarms, critical when false positives lead to unnecessary intervention, client anxiety, or irreversible decisions. Consider canine brucellosis: a false positive could lead to euthanasia and significant concern about zoonotic transmission to the family.

Note that specificity and precision are not equivalent, they answer fundamentally different questions.[42] Specificity concerns performance on true negatives (of all healthy patients, how many were correctly identified as healthy?) whereas precision concerns reliability of positive predictions (of all patients flagged as diseased, how many actually were?). A system can exhibit high specificity with low precision, or vice versa, depending on disease prevalence.

Clinicians also use positive *predictive value (PPV)* and *negative predictive value (NPV):*

$$PPV = \frac{TP}{TP + FP} = Precision$$

$$NPV = \frac{TN}{TN + FN}$$

PPV is mathematically identical to precision; the clinical and ML communities use different terminology for the same quantity.[43]

The Sensitivity-specificity Tradeoff

Sensitivity and specificity are inversely related at any given decision threshold.[44] Adjusting an AI to catch more true positives (high sensitivity) typically increases false positives (lower specificity). Developers chose thresholds based on the relative costs of different errors, but these choices may not align with a specific clinical context, so it is critical to consider this independently.

A screening tool optimized for sensitivity will flag borderline cases, generating false positives that require follow up. A confirmatory tool optimized for specificity will miss borderline cases but provide high confidence when positive. Neither optimization is inherently correct; the appropriate threshold depends on clinical application.[44]

The Prevalence Problem

Precision (equivalently, PPV) depends heavily on disease prevalence in ways that sensitivity and specificity do not.[42] This is why clinical researchers often favor sensitivity and specificity, they remain stable across populations with different disease rates, enabling comparison across settings.

Consider an AI with 95% sensitivity and 95% specificity applied to 2 populations (**Table 2**):

The same system, identical sensitivity and specificity, yields 95% precision in one population and 49% in another.[42] If a tool reports precision from a validation set

Table 2
Demonstration on effects of prevalence on precision with 2 populations that have identical specificity and sensitivity

	Population A (50% Prevalence)	Population B (5% Prevalence
True positive	475	47
False negative	25	3
True negative	475	902
False positive	25	48
Precision (PPV)	475/(475 + 25) = 95%	47/(47 + 48) = 49%

with artificially balanced classes, real-world performance in low-prevalence settings will be substantially worse. Dataset balancing, where researchers intentionally include roughly equal numbers of positive and negative cases, is standard practice in ML development because it improves model training. However, it creates validation conditions that do not reflect clinical reality.

This matters for veterinary applications where many conditions are rare. Using the osteosarcoma example, an AI tool may demonstrate excellent precision in a validation study using university hospital data as they re enriched with positive cases; it may produce mostly false positives in general practice where true prevalence is low. When precision or F1 are reported without prevalence information, caution is needed.

Translating Between Frameworks

In veterinary AI tool evaluation both clinical and computers science terminologies are used.[43] ML-originated tools (eg, natural language processing systems looking at text, general computer vision) typically report precision, recall, and F1. Clinically validated tools (eg, diagnostic imaging, screening applications) typically report sensitivity, specificity, and PPV/NPV. An ML paper reporting only precision and recall provide no direct information about specificity. A clinical paper reporting sensitivity and specificity enables precision calculation only if prevalence is known. Ideally, the underlying data necessary for a confusion matrix is provided. This allows better comparison when evaluating tools across different validation studies and ensures that the equivalent metrics are being compared on populations with comparable prevalence.

Area Under the Receiver Operating Characteristic Curve: Threshold-independent Performance

Every AI classification system operates with an internal threshold determining how suspicious it must be before flagging a case as positive. This threshold is not fixed and represents a design choice with direct clinical consequences. Lower that threshold and the system flags more true disease (higher sensitivity) but generates more false alarms (lower specificity). Raise the threshold and false positives decrease but false negatives increase. Every threshold embodies a tradeoff; there is no setting that optimizes both simultaneously.

The receiver operating characteristic (ROC) curve makes this tradeoff space explicit.[45] Formally, the ROC curve plots sensitivity (true positive rate) against 1—specificity (false positive rate) across all possible thresholds (**Fig. 1**). Each point on the curve represents a different operating threshold: the upper left corner (0, 1) represents ideal performance, perfect sensitivity with perfect specificity, while the diagonal line represents random chance (AUC = 0.5). Any useful classifier should perform

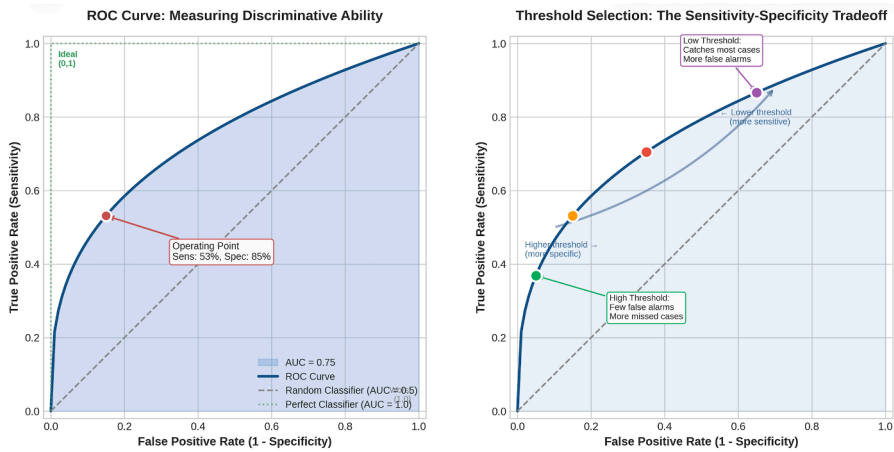


Fig. 1. (*Left*) An ROC curve with AUC = 0.75 showing the AUC shaded in blue. The operating point indicates the chosen threshold (sensitivity 53%, specificity 85%). The dashed diagonal represents random chance. (*Right*) How threshold selection creates the sensitivity-specificity tradeoff: lowering the threshold increases sensitivity but reduces specificity.

above this diagonal, with curves bowing further toward the upper left corner indicating better discriminative ability.

The area under the ROC curve (AUC-ROC) summarizes this curve as a single value quantifying discriminative ability independent of threshold selection. AUC answers the question, "Given one case with disease and one without, how often will the system correctly assign higher suspicion to the diseased case?" An AUC of 0.90 means correct ranking occurs 90% of the time.[45] **Fig. 2** illustrates how classifiers with different AUC values exhibit varying discriminative abilities.

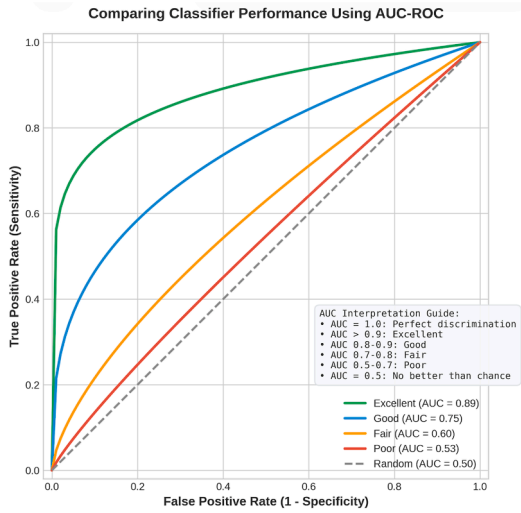


Fig. 2. Comparison of classifiers with different discriminative abilities. Higher AUC values correspond to curves that bow further toward the upper left corner, indicating better separation between positive and negative cases. The interpretation guide shows standard benchmarks for AUC assessment.

General AUC interpretation guidelines are as follows:

- AUC = 1.0: Perfect discrimination
- AUC greater than 0.9: Generally considered excellent
- AUC 0.8 to 0.9: Good
- AUC 0.7 to 0.8: Fair
- AUC = 0.5: No better than chance

AUC is useful for comparing systems but has significant limitations that must be understood.

First, AUC measures discrimination, whether the system can distinguish diseased from healthy cases, rather than classification accuracy at any specific operating point. An AUC of 0.95 does not mean 95% accuracy; it means that when presented with one diseased and one healthy case, the system assigns higher suspicion to the diseased case 95% of the time. Clinical deployment requires selecting a specific threshold, at which point the sensitivity-specificity tradeoffs reassert themselves. A system with excellent AUC may still perform poorly at the threshold chosen for deployment.

Second, AUC can mislead when disease prevalence is low (a situation ML researchers call *class imbalance*), common in veterinary applications where most patients do not have the condition being screened for.[46] The ROC curve treats sensitivity symmetrically, which can obscure poor positive predictive performance in imbalanced datasets. In such settings, precision-recall (PR) curves and the corresponding area under the PR curve may provide more informative summaries.[41] A system with high AUC-ROC may produce unacceptably low precision at any practice operating threshold when the positive class is rare.

The practical implication is clear: when AUC is reported, performance metrics at the specific threshold used for deployment are needed for evaluation. AUC alone, without accompanying sensitivity, specificity, and precision at the operational threshold, provides insufficient information for clinical evaluation.

Calibration: when Confidence Matches Reality

Many AI systems output not just predictions but confidence scores such as *85% probability of pneumonia* rather than simply *pneumonia detected*. These probability estimates are useful only if they mean what they claim to mean. A system calibrated well produces confidence scores that match actual frequencies: if the system assigns 80% confidence to 100 predictions, approximately 80 should prove correct.

Calibration matters because confidence scores often inform clinical decisions. A finding flagged with 95% confidence may prompt different action than one flagged at 60%. If these numbers are unreliable, they mislead rather than inform.

Poor calibration is common in deep learning models, which frequently exhibit systematic overconfidence.[47] An AI reporting *95% confident this is osteosarcoma* may be correct far less than 95% of the time since the number reflects the model's internal mathematics rather than true diagnostic probability. This is not merely a minor technical concern; it directly affects how clinicians interpret and act on AI outputs.

Calibration can be assessed through reliability diagrams, which plot predicted probability against observed frequency (**Fig. 3**), and quantified through metrics such as the Brier score or expected calibration error (for both, lower values indicate better calibration).[47] When underlying probability scores are inaccessible, as with many large language models (LLMs), alternative approaches include prompting the model to express confidence verbally or generating multiple responses and treating inconsistency as a signal of uncertainty.[48] These methods remain less validated than traditional calibration assessments.

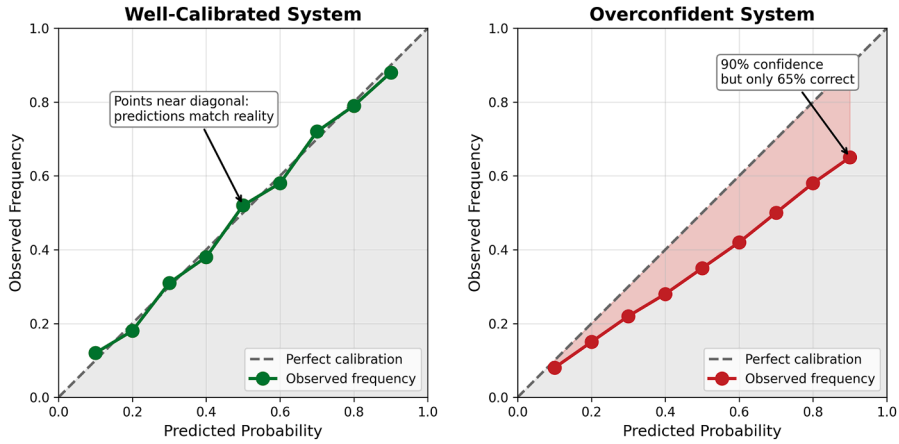


Fig. 3. Reliability diagrams comparing a well-calibrated system (*left*) with an overconfident system (*right*). Points along the diagonal indicate good calibration; deviation below the diagonal indicates overconfidence.

When a tool provides confidence scores, without an evaluation of the calibration, it should be treated as relative rankings (higher means more suspicious) rather than true probabilities.

Why Accuracy Is Misleading

Accuracy is the proportion of all predictions that are correct and is the most commonly reported metric and frequently the most misleading.[49]

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Consider this example. An AI tool is developed to detect a condition that has 5% prevalence in the target population. A system that predicts *negative* for every case, ignoring all input data entirely, achieves 95% accuracy. It has learned nothing, detects nothing, and provides zero clinical value. Yet by the accuracy metric, it appears highly successful.[49] This is not a contrived scenario. Many clinically important conditions are rare, and validation datasets are often constructed with artificial balance (50% positive and 50% negative) that inflates accuracy relative to real-world performance. A system reporting 90% accuracy on a balanced validation set may perform very differently when deployed in a population where true prevalence is 2%.

The practical implication is straightforward: when evaluating AI tools, before being considered for use, it should be required to provide sensitivity and specificity (or precision and recall) reported separately for each class. These metrics reveal how the system performs on positive and negative cases independently. Accuracy may be reported for completeness, but it should never be the primary metric, and comparisons of accuracy across datasets with different prevalence rates are not meaningful. Aggregate accuracy alone, without breaking down the specifics of each class and not having prevalence information, is insufficient for clinical assessment. Its presence as the primary reported metric, without accompanying performance of each class, should prompt skepticism about validation rigor.

INTERANNOTATOR AGREEMENT: THE PERFORMANCE CEILING

A critical but often overlooked aspect of AI evaluation is the quality of the *ground truth* labels against which performance is measured.

The Labeling Problem

Supervised AI learns from labeled examples. For example, radiographs annotated as *pneumonia present* or *normal*, or histopathology slides classified by tumor grade. These labels are generated by human experts. If experts disagree about correct labels, AI performance is fundamentally constrained by that disagreement. A system cannot be evaluated as better than its training labels when those labels constitute the only available ground truth.

Interannotator agreement (IAA) quantifies consistency among human labelers.[50,51] The most common measure is Cohen's Kappa, which calculates agreement between 2 annotators while correcting for chance:

$$\kappa = \frac{p_o - p_e}{1 - p_e}$$

Where p_o is observed agreement and p_e is chance-expected agreement. Fleiss' Kappa extends this calculation to more than 2 annotators.

Interpretation guidelines are as follows:[50]

- $\kappa > 0.80$: Excellent agreement
- κ 0.60 to 0.80: Substantial agreement
- κ 0.40 to 0.60: Moderate agreement
- $\kappa < 0.40$: Poor agreement

These thresholds are conventions rather than absolute standards but provide useful benchmarks for assessing label quality. However, IAA metrics have notable limitations: different statistics can yield substantially different scores for the same data, and inherently complex judgment tasks produce lower agreement regardless of label quality, making context essential when interpreting these values.[52]

Why Interannotator Agreement Constrains Evaluation

Consider a concrete example: 2 board-certified radiologists reviewing the same set of thoracic radiographs for pneumonia agree 85% of the time ($\kappa \approx 0.70$). The remaining 15% represents cases where expert opinion genuinely diverges, potentially due to borderline presentations, ambiguous findings, or cases where reasonable specialists reach different conclusions.

An AI system trained and evaluated on labels from one radiologist cannot be meaningfully said to *exceed* 85% performance. If the system achieves 95% agreement with Radiologist A, it may simply be achieving 80% agreement with Radiologist B. Without knowing which radiologist is *correct* in disputed cases, often an unanswerable question, we cannot determine whether the system has learned genuine diagnostic accuracy or merely one expert's labeling tendencies.

This has direct implications for interpreting validation studies. AI performance should be contextualized against IAA, not assumed perfect ground truth.[51] A system achieving 88% accuracy against labels with 85% IAA is performing at approximately the level of expert disagreement. A system achieving 95% accuracy against labels with 70% IAA warrants scrutiny, and it may indicate methodological problems such as test set contamination (training on data inadvertently included in the evaluation set) or label leakage (the model learning to predict labels from artifacts in the data rather than clinical features) rather than genuinely superior performance.

Low interannotator agreement signals task ambiguity

When experts cannot agree, the problem may lie not with the AI but with the clinical concept itself. Some diagnostic categories are inherently fuzzy; their boundaries depend on threshold choices that reasonable clinicians make differently. In such cases, the appropriate response may be task redefinition rather than algorithmic improvement.

In rare cases, AI might genuinely detect patterns imperceptible to human experts, as demonstrated by deep learning systems that predict cardiovascular risk factors from retinal images that clinicians cannot visually assess.[53] Validating such claims requires outcome-based validation, correlating predictions with histopathology, treatment response, or survival, rather than relying on expert labels as ground truth.[54]

Interannotator agreement establishes evaluation ceilings

If IAA calculation is not performed before AI evaluation, there is no way to determine whether reported performance represents genuine capability or reflects artifacts of how labels were generated.

Implications for Veterinary Artificial Intelligence

Veterinary AI faces challenges in establishing reliable ground truth:

Limited specialist availability

Board-certified veterinary radiologists, pathologists, and cardiologists are scarce relative to case volume. Large-scale labeling efforts may rely on general practitioners whose diagnostic accuracy differs from specialist consensus. An expert in canine cardiology may not be an expert in feline cardiology. Labels generated without appropriate species-specific expertise may reflect knowledge gaps rather than ground truth.

Retrospective labeling limitations

Training labels derived from clinical records use outcomes (eg, histopathology results, response to treatment, clinical progression) as proxies for diagnostic truth. These proxies introduce systematic biases, cases that proceeded to biopsy may be consistently different from those managed conservatively and treatment response conflates diagnosis accuracy with treatment selection.

When evaluating AI tools, the relevant questions must be asked: How were training labels generated? By whom? Was IAA measured and reported? Tools validated against labels from nonspecialists, or without IAA assessment, provide insufficient evidence for clinical adoption. The absence of IAA reporting should raise concerns about validation rigor.

VALIDATION HIERARCHY AND EXTERNAL VALIDITY

Types of Validation

Validation exists on a hierarchy of strength:

Internal validation tests performance on hold out data from the same source as training data. This demonstrates the model learned patterns in that dataset but says nothing about generalizability.

External validation tests on genuinely independent data, from a different institution, time period, or population. This provides evidence of transportability.

Prospective validation tests on new cases collected after model development, under real clinical conditions. This is the strongest evidence but rarely performed.

Multisite validation across diverse institutions with different equipment, populations, and practices provides the most confidence in generalizability.

The Generalization Gap

Published evidence demonstrates consistent *generalization gaps* where AI performance degrades on external data.[55] A systematic review of deep learning algorithms for radiologic diagnosis found that the vast majority (81%) of externally validated models showed decreased performance compared to internal validation, with nearly half (49%) showing at least a modest decrease of 0.05 or more in AUC, and nearly a quarter (24%) showing substantial drops of 0.10 or greater.[55]

Several factors drive these performance gaps. Disease prevalence, case demographics, and severity distributions differ between institutions. A model trained where a condition is common may encounter fundamentally different patient populations elsewhere. Image characteristics also vary considerably across sites due to differences in equipment, positioning protocols, and image quality standards. Labeling practices introduce additional variability, as what one institution calls a particular finding may not precisely match another's diagnostic criteria. Perhaps most problematic are spurious correlations, where models learn to rely on features that happen to predict outcomes in training data but have no true diagnostic value. These might include institutional documentation templates, equipment-specific artifacts, or imaging protocols unique to the training environment.

For LLMs, the relationship between memorization and generalization differs by task type: knowledge retrieval tasks depend heavily on whether information appeared in training data, while reasoning tasks show greater generalization, with performance less tied to training data frequency.[56,57]

Minimum Validation Requirements

For clinical deployment, certain validation standards should be considered nonnegotiable. Validation of any AI product being used in a clinic should include the following:

- External validation on independent data
- Disclosure of validation population characteristics (eg, disease prevalence, referral vs primary care settings)
- Performance on relevant subgroups (eg, species, breeds, disease severity)
- Confidence intervals reflecting estimate precision (which requires adequate sample sizes)

Developer-reported metrics without independent verification warrant skepticism. Peer-reviewed publication provides more confidence than marketing materials, but even published studies may have methodological limitations.

MODALITY-SPECIFIC CONSIDERATIONS

Artificial Intelligence Scribes and Documentation

AI scribes generate Subjective, Objective, Assessment, Plan (the standard clinical documentation format) notes from consultation audio using speech recognition and LLMs. Unlike diagnostic AI, *ground truth* is partly subjective as note quality involves clinical completeness, appropriate terminology, and accurate representation of the encounter.

Evaluation considerations specific to AI scribes include the following:

Hallucination risk: Generative AI can produce plausible but fabricated content, and systematic verification against audio recordings is essential.[58] Studies evaluating LLM-generated clinical documentation have observed hallucination rates of 1.47%

and omission rates of 3.45%, with errors potentially carrying significant clinical safety and legal implications.[58]

Terminology accuracy: Does the tool handle veterinary-specific terminology, abbreviations, and species-specific language?

Completeness metrics: What proportion of clinically relevant information from encounters is captured?

The evidence base for veterinary AI scribes remains limited, with few peer-reviewed validation studies.

Diagnostic Imaging Artificial Intelligence

Digital imaging AI represents the most mature veterinary application, spanning radiography, echocardiography, and other modalities. However, the peer-reviewed literature remains relatively sparse with few publications using ML for imaging-associated tasks across veterinary clinical and biomedical research.[6]

Evaluation considerations include the following:

Finding coverage: Tools detect finite lists of abnormalities. Conditions outside that list will not be identified.

Species/breed validation: Anatomic conformation varies dramatically (thoracic shape in radiography, cardiac anatomy in echocardiography) and requires validation across relevant populations, including breed-specific conditions such as cardiomyopathies.

Sensitivity vs. specificity tradeoffs: Understanding how the tool is optimized, whether for screening (high sensitivity) or confirmation (high specificity).

Comparison to radiologist standard: Performance should be benchmarked against board-certified interpretation, with inter-reader agreement reported.[59]

Pathology and Cytology Artificial Intelligence

Pathology AI applications include tumor grading, lymphoma classification, and automated cell counting. Unique considerations:

Preparation variation: Staining protocols and slide preparation affect image characteristics.

Scanner calibration: Different whole-slide imaging platforms produce different outputs.

Interpathologist agreement: The gold standard itself shows variability; AI performance should be contextualized against expert agreement.

SUMMARY

AI tools offer substantial potential to improve veterinary medicine. Realizing this potential requires evaluation literacy, and understanding metrics such as sensitivity, specificity, precision, recall, F1 score, AUC, and AUC-ROC, the role of IAA, as well as the critical importance of external validation.

The core questions are straightforward: What is the sensitivity and specificity? On what population? Compared to what expert baseline? With what external validation? These are not obstacles to adoption but prerequisites for responsible adoption.

In the absence of regulatory oversight, the profession must develop and apply rigorous standards. The framework presented here, grounded in quantitative evaluation metrics and practical checklists, equips veterinary professionals to make informed decisions. As AI proliferates, these evaluation skills become as essential as any other clinical competency.

CLINICS CARE POINTS

- Evaluating artificial intelligence (AI) tools requires understanding core performance metrics (sensitivity, specificity, precision, recall, F1 score, area under the curve, and area under the receiver operating characteristic curve) and recognizing that reported performance depends heavily on the population tested.
- AI performance is fundamentally limited by interannotator agreement among the expert labelers who created the training data, a concept often overlooked in validation studies.
- External validation on independent datasets is essential, as AI tools frequently show degraded performance when deployed outside their original training environment, and without regulatory oversight, clinicians bear responsibility for critical evaluation before adoption.

DISCLOSURE

B. Hur is employed by Veterinary Information Network. This employment did not influence the content of this article. The remaining authors have nothing to disclose.

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