Computer Vision and Deep Learning in Small Animal Cytology and Slide Review

Candice P. Chu, DVM, PhD

KEYWORDS

• AI literacy • Computer vision • Convolutional neural networks • Cytology
• Deep learning • Hematology • Machine learning • Position statement

KEY POINTS

- Cytology is a commonly used diagnostic method in veterinary medicine, but slide review is time consuming and imperfect, with interobserver reproducibility/agreement that may differ depending on task, lesion type, and diagnostic experience. The development of artificial intelligence (AI), particularly computer vision (CV), can further accelerate the workflow and potentially reduce interobserver variability and misdiagnosis.
- This review introduces CV and its application in small animal cytology and slide review. It covers recent studies, commercial products, regulatory considerations, educational needs, and current concerns.
- CV enables computers to interpret, understand, and analyze visual data, and convolutional neural network (CNN) algorithms are commonly used to analyze image and video content and perform CV tasks such as image-level classification, object detection, and semantic and instance segmentation.
- Among small animal slide review AI studies published by 2025 (n = 10), more than half of the studies focused on canine blood smears, and most used CNN algorithms such as RetinaNet and different versions of YOLO (You Only Look Once); performance metrics varied, even for the same CV task type.
- The application of CV tools in veterinary medicine faces three main challenges: the absence of regulation on AI usage, the lack of transparency in commercial products, and inadequate education and training. Veterinarians should never assume AI outputs are accurate, and any medical decisions should be justified by professional knowledge.

INTRODUCTION

Cytology is a commonly used diagnostic method in veterinary medicine because it is low cost, minimally invasive, and has a relatively short processing time compared with tissue biopsy. The traditional workflow for slide review is as follows: veterinary practitioners perform venipuncture to draw blood or use fine-needle aspirates, imprints, and

Department of Veterinary Pathobiology, College of Veterinary Medicine & Biomedical Sciences, Texas A&M University, College Station, TX, USA
E-mail address: cchu@cvm.tamu.edu

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Abbreviations	
AAVSB	American Association of Veterinary State Boards
ACVIM	American College of Veterinary Internal Medicine
ACVP	American College of Veterinary Pathologists
ACVR	American College of Veterinary Radiology
AI	artificial intelligence
ASVCP	American Society for Veterinary Clinical Pathology
BVA	British Veterinary Association
CNN	convolutional neural network
CV	computer vision
CVO	College of Veterinarians of Ontario
ECVDI	European College of Veterinary Diagnostic Imaging
FDA	Food and Drug Administration
ML	machine learning
YOLO	You Only Look Once

tape preparations to collect cells from tissue, prepare blood or cytology smears, stain one of the slides with an in-house aqueous Romanowsky stain (eg, Diff-Quik), and ship the stained and unstained glass slides to a diagnostic laboratory for methanol-based Romanowsky staining (eg, Wright or Giemsa stains). In the diagnostic laboratory, veterinary clinical pathologists, who are board-certified specialists trained through a 3 year residency, perform slide evaluation. With the development of digital cytology, this evaluation can be performed either by light microscopy or by review of scanned digital slides.[1] In both approaches, cytologists will examine sample quality, cell type, cellular morphology, and the presence of infectious agents to reach a final interpretation and issue a report.

Blood smear or cytology slide evaluation is time-consuming and imperfect. Several studies have examined intraobserver and interobserver reproducibility and agreement in smear review, which can vary depending on task, lesion type, and diagnostic experience.[2–7] Advances in artificial intelligence (AI), particularly in computer vision (CV), may further accelerate the workflow and potentially reduce interobserver variability and misdiagnosis. This review provides an introduction for veterinary cytologists, practicing veterinarians, and veterinary students seeking a foundational understanding of CV and its application in small animal cytology, including blood smear examination. It covers recent studies, commercial products, regulatory considerations, educational needs, and current concerns.

FUNDAMENTALS OF COMPUTER VISION FOR VETERINARY CYTOLOGY

In brief, AI refers to the ability of computers to simulate human intelligence by performing tasks such as learning, reasoning, problem-solving, perception, and language understanding. Under the umbrella term of AI, machine learning (ML) refers to a computer's ability to learn from large amounts of data without relying on rule-based instructions. Deep learning is a subarea of ML that utilizes different model architectures, including artificial neural networks, convolutional neural networks (CNNs), recurrent neural networks, and transformers.[8] Readers who wish to obtain a basic overview of different neural networks are encouraged to read Neal and colleagues' review of AI in *Veterinary Clinical Pathology*.[8]

This review focuses on CV, a specialized application domain within AI that is defined by the analysis of visual data rather than by a distinct class of algorithms. While AI and ML encompass methods applicable to many data modalities, CV specifically applies these methods to images and videos. In veterinary medicine, CV represents one of the

primary practical applications of AI and has been most widely adopted in radiology and pathology. CV algorithms can analyze radiographs,[9] cytology smears,[10] and pathology sections to count cells and mitotic figures, detect abnormalities, and aid in diagnosis.[11,12]

CNN algorithms are the most commonly used model architecture for common CV tasks, such as image-level classification, object detection, and both semantic and instance segmentation.[13] These tasks vary in their level of detail, ranging from broad image-level labels to precise pixel-wise delineations, and the choice of task depends on the specific diagnostic or research question being addressed (**Fig. 1**). Image-level classification puts an entire image into one of the predefined categories. For example, Pacholec and colleagues evaluated the performance of 14 CNN models for classifying 600 canine lymph node cytology images into 2 categories, canine large cell lymphoma and non-lymphoma, and found that models trained on high-magnification (1000 $\times$) images achieved the highest diagnostic performance, while image color versus grayscale had minimal impact and model performance plateaued at approximately 150 images per category.[10] Object detection localizes different objects (ie, cells) in an image using bounding boxes and classifies them into predefined categories. For instance, Bertram and colleagues used the CNN algorithm RetinaNet to detect and assign hemosiderin grades to 218,003 macrophages across 52 whole slide images, demonstrating that the automated approach achieved higher diagnostic accuracy and markedly improved reproducibility compared with human experts in cytologic scoring of equine exercise-induced pulmonary hemorrhage.[14] However, object detection models are limited to cell localization. For research questions that require cell boundary delineation, semantic segmentation models can address the pixel-level classification problem, yielding detailed separation between cells and the background. In Wulcan and colleagues' work, they used semantic segmentation to classify pixels into different intestinal layers, such as epithelium, lamina propria, intestinal lumen, and others in histopathology sections.[11] However, the standard semantic segmentation task does not classify the cells. If a task involves outlining and classifying each cell, it is called instance segmentation. Accordingly, in the same study, Wulcan and colleagues also used instance segmentation to identify lymphocyte nucleus boundaries.[11] For more details about CV tasks and their performance metrics, readers are encouraged to consult articles by Pacholec and colleagues[15] and Maier-Hein and colleagues.[13] The latter also provided an online metrics selection tool for image analysis studies available at https://metrics-reloaded.dkfz.de/.

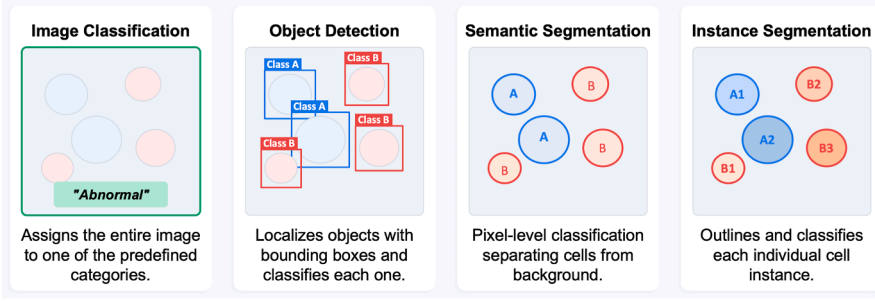


Fig. 1. Overview of common computer vision tasks for cell image analysis (image-level classification, object detection, and both semantic and instance segmentation), ordered by increasing level of detail from left to right.

SCIENTIFIC PROGRESS AND GUIDELINES FOR PUBLICATION

In human cytology, CV most commonly applies to gynecologic cytology,[16,17] cervical cancers,[18,19] urine sediment,[20] and effusion cytology.[21] To comprehensively discuss the current research progress of CV in small animal cytology, including blood smear examination, a PubMed search was conducted for all articles up to December 31, 2025. The search covered articles with titles or abstracts that include the following keywords with Boolean logic: "(cytology[Title/Abstract] OR cytologic[Title/Abstract] OR blood smear[Title/Abstract] OR blood smears[Title/Abstract] OR blood cell[Title/Abstract]) AND (deep learning[Title/Abstract] OR convolutional neural network[Title/Abstract] OR artificial intelligence[Title/Abstract] AND (canine[Title/Abstract] OR dogs[Title/Abstract] OR feline[Title/Abstract] OR cats[Title/Abstract] OR veterinary[Title/Abstract] OR veterinarian[Title/Abstract])." The same search logic, not limited to titles and abstracts, was applied in a Google Scholar search. After excluding preprints, reviews, nonsmall animal, nonslide evaluation, and nonveterinary studies, 10 articles were identified for discussion. **Table 1** presents an overview of these papers.

More than half of the studies focused on canine blood smears, aiming to enumerate and classify blood cells,[24,27] locate hemoparasites,[22,28] and identify erythrocyte morphology.[29,30] Most studies used CNN algorithms such as RetinaNet and different versions of YOLO (You Only Look Once), which are commonly used in such tasks.[31,32] In these studies, variable performance metrics were used to evaluate model performance even for the same CV task type.

In veterinary medicine, ongoing efforts are being made to increase the transparency and reproducibility of AI-based automated image analysis. Bertram and colleagues proposed an AI-based automated image analysis reporting guidelines for *Veterinary Pathology*.[33] The guidelines provided a 9 point checklist in the supplemental material that encourages researchers to report detailed materials and methods, including information on image acquisition/processing/annotation, data partitioning for model training and validation, and model performance evaluation. On the other hand, Pacholec and colleagues emphasized the importance of external validation of AI tools.[34] These factors, such as calibration, uncertainty, runtime monitors, robustness, repeatability, and generalizability, may be absent in some of the aforementioned studies, as these were often early, proof-of-concept studies. Practicing veterinarians are encouraged to prioritize adopting AI tools accompanied by scientific publications. The following sections on Regulatory Considerations and Industrial Implementation offer practical guidance to help practitioners make informed purchasing decisions about AI tools.

REGULATORY CONSIDERATIONS

In human medicine, the US Food and Drug Administration (FDA) has implemented premarket requirements for AI-enabled medical devices.[35] Its final guidance was published in December 2024 and updated on August 18, 2025.[36] Currently, there are no premarket requirements for AI-enabled devices in veterinary medicine in North America. However, many veterinary professional societies have published position or policy statements to address the development and responsible use of AI tools (**Table 2**).

Almost all professional societies recognized an urgent need for regulatory bodies to establish guidelines on veterinary AI tools.[37–42,44] In response to the lack of centralized regulation, the American Association of Veterinary State Boards (AAVSB) and the Canadian Veterinary Medical Association noted that veterinary practitioners who use AI tools must understand that the FDA-approved AI-enabled human devices do not cover animal use.[37,43] The California Veterinary Medical Association supports

Table 1
Overview of computer vision studies in small animal slide evaluation published by 2025 (n = 10)

Author, Year	Species	Biological Samples	Labeled Image/Cell Size	Neural Network	Algorithm	Task	Performance Metrics
Baruah et al.[22] 2025	Dog	Blood smears	1066 images	CNN	Comparing ResNet, EfficientNet, and DenseNet	Image-level classification	Accuracy, precision, recall, F1-score, specificity, sensitivity,
Caputa et al.[23] 2024	Dog[a]	Unspecified tissue slides	1192 images	Transformer, CNN	Superresolution models: SwinIR, BSRGAN, RealSRGAN; CNN model: Cascade Mask R-CNN with ResNeSt101	Semantic segmentation	Average precision, average recall, mAP
Jeong et al.[24] 2024	Dog	Blood smears	486 images (18,542 cropped WBC, 46,612 augmented WBCs)	CNN	Detection: YOLO-v8, RetinaNet, Faster-RCNN, YOLO-v5; classification: DenseNet, VGG, ViT, ResNet	Object detection	Precision, recall, F1-score, mAP

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Table 1
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Author, Year	Species	Biological Samples	Labeled Image/Cell Size	Neural Network	Algorithm	Task	Performance Metrics
Lapsina et al.[25] 2024	Dog	Cerebrospinal fluid slides	62 WSI (approximate 6200 cells)	Unspecified	Unspecified deep learning neural network algorithm	Object detection	Spearman's rank correlation coefficient, Passing–Bablok regression, Bland–Altman plot
Marzahl et al.[26] 2022	Cat	Bronchoalveolar lavage fluid slides	7 WSI (20,198 cells)	CNN	RetinaNet	Object detection	mAP
Morissette et al.[27] 2024	Dog and cat	Blood smears	119 WSI (phase A), 161 WSI (phase B), 59 WSI (phase C)	CNN	YOLOv3	Object detection	Average precision, specificity, sensitivity, precision-recall curve area, Passing–Bablok regression
Nejad et al.[28] 2022	Dog	Blood smears	175 images	CNN	U-Net	Semantic segmentation, image-level classification	Accuracy, sensitivity, specificity, AUC-ROC

Pacholec et al.[10] 2025	Dog	Lymph node cytology slides	600 images	CNN	Inception-v3	Image-level classification	Accuracy, precision, recall, AUC-ROC, F1-score, true positive, false positive, precision-recall curve area
Pasupa et al.[29] 2020	Dog	Blood smears	3392 images containing single RBC	Semi-deep convolutional GANs, CNN	Unspecified	Image-level classification	Accuracy
Pasupa et al.[30] 2020[b]	dog	blood smears	3392 images containing single RBC	CNN	ResNet, DenseNet	Image-level classification	Accuracy, F1-score, AUC-ROC

Abbreviations: AUC-ROC, area under the receiver operating characteristic curve; GAN, generative adversarial network; mAP, mean average precision; RBC, red blood cell; WSI, whole slide image.

[a] The species was not specified in the publication, but presumed to be a dog due to the description: "Our prior work has focused on age classification [1], object segmentation [2], and detection [3] in the context of cytology imaging for canines."[23]

[b] Published online: 15 February 2020

Table 2
List of artificial intelligence position or policy statements published by veterinary organizations (n = 9)

Organization	Year	Title	Description Regarding the Use of Veterinary AI Tools
USA			
American Association of Veterinary State Boards (AAVSB)	March 2025	Regulatory Considerations of the Use of Artificial Intelligence in Veterinary Medicine[37]	• Emphasizes that licensees must understand AI risks and limitations, maintain transparency, safeguard client data privacy, obtain informed consent, and comply with their jurisdiction's Veterinary Practice Act.
American College of Veterinary Radiology (ACVR) and European College of Veterinary Diagnostic Imaging (ECVDI)	March 2025	American College of Veterinary Radiology and European College of Veterinary Diagnostic Imaging position statement on artificial intelligence[38]	• Focuses on AI in veterinary diagnostic imaging and radiation oncology. • States that "no commercially available AI products for veterinary diagnostic imaging currently meet required standards for transparency, validation, or safety." • Calls for peer-reviewed research and third-party evaluations before adoption.
Georgia Veterinary Medical Association (GVMA)	November 2024	Policy Statement: Use of AI in Vet Med[39]	• Describes AI technologies as available in the veterinary space to provide support, but states no existing technology replaces professional judgment, spectrum-of-care advising, evaluation of the human-animal bond, or empathy. • Stresses that AI tools must not expose client information or medical records to foundation models or large language models without express consent.
California Veterinary Medical Association (CVMA)	July 2024	CVMA Policy on the Use of Artificial Intelligence in Veterinary Medicine[40]	• Recognizes AI technologies are available to provide support to veterinarians but states no existing technology replaces professional judgment and clinical expertise. • Supports implementing FDA regulations (already used in human medicine) for veterinary AI and lists concerns including incorrect diagnosis/treatment, data security, source bias, and deskilling.

Canada			
College of Veterinarians of Ontario (CVO)	December 2024	Use of Medical Devices Enabled by Artificial Intelligence in the Practice of Veterinary Medicine[41]	• A companion guide to the CVO's earlier position statement.[42] • Notes that no medical device for animal health care has oversight or approval from a regulatory authority like Health Canada.
College of Veterinarians of Ontario (CVO)	March 2024	Embracing Innovation and the Digital Age in Veterinary Medicine[42]	• Defines "Software as a Medical Device (SaMD): software intended to be used for one or more medical purposes that perform these purposes without being part of a hardware medical device (eg, mobile app)." • Highlights the lack of government regulatory oversight for these technological tools and emphasizes practitioner accountability in selecting and integrating them.
Canadian Veterinary Medical Association (CVMA)	October 2023	Artificial Intelligence in Veterinary Medicine[43]	• Notes that AI applications are expanding rapidly in veterinary medicine with a wide range of uses, including many adapted from human medicine. • Warns that commercial AI systems for veterinary diagnostics may be brought to market with little or no supporting evidence due to a lack of regulatory oversight in Canada.
UK			
British Veterinary Association (BVA)	Jan 2026	BVA Policy Position on Artificial Intelligence in the Veterinary Profession[44]	• Describes AI broadly as a significant emerging technology across the veterinary profession, spanning clinical practice (including diagnostics), education, research, epidemiology, government, administrative tasks, and practice management. • Frames AI as a tool to support veterinary professionals, not replace them.
Royal College of Veterinary Surgeons (RCVS)	May 2024	RCVS AI Roundtable Report[45]	• Covers AI use in clinical practice, veterinary data, higher education, and regulatory risk management. • Aims to establish an initial direction for regulating AI within the veterinary professions.

implementing existing human FDA regulations in veterinary medicine.[40] Also, the American College of Veterinary Radiology (ACVR), the European College of Veterinary Diagnostic Imaging (ECVDI), the Canadian Veterinary Medical Association, and the British Veterinary Association (BVA) all remind veterinary users that the legal responsibility for decisions made by AI tools remains undetermined, but is likely to fall on veterinarians, not developers.[37,38,43,44]

Therefore, one must ask what the best practices are for developing, selecting, and using AI tools for veterinary cytology. Although the American College of Veterinary Pathologists (ACVP) and the American Society for Veterinary Clinical Pathology (ASVCP) have not yet published positions or policy statements on AI, similar documentation from other professional societies may provide some guidance. For AI developers, ACVR and ECVDI support the development of AI that follows good ML practice[46] and transparency for ML-enabled devices[47]; they note that AI systems that do not follow these principles should not be used in veterinary practice.[38] In addition, peer-reviewed publications demonstrating the clinical utility of AI systems are strongly recommended, as they are essential for building trust.[38]

INDUSTRIAL IMPLEMENTATION

The development of digital cytology services,[1] either through mobile phone-captured images or in-clinic scanners, has enabled faster reporting times, with some options for pathologist results within hours.[48–50] Meanwhile, some diagnostic companies have begun embracing AI technologies to further shorten turnaround time. Among the major diagnostic companies, one company does not mention AI on its digital cytology website.[50] Another company uses AI to recognize slides and recommend the area of interest for evaluation, but explicitly states that the AI does not interpret cells on slides.[48] One company offers AI lymphoma detection and states that every result is reviewed by a board-certified veterinary clinical pathologist.[51] Another company offers AI-powered applications for urine sediment, dermatology (ear cytology), parasitology (fecal cytology), blood smears, and cytology of common lymph nodes and skin/subcutaneous masses.[52] Submitters can select either an AI readout or a pathologist readout. For AI readouts, their product one-pager and hospital resource guide state that digital slide images can be further sent to clinical pathologists as needed for an additional fee, indicating that the initial AI results are cheaper and not supervised.[53] It is worth noting that no peer-reviewed publications were cited to support the clinical performance of these AI products.[51,52] Veterinary clinical pathologists have a specialized skill set for evaluating and validating traditional diagnostic tests.[54] Accordingly, AI-enabled diagnostic tools should be subject to transparency and validation standards, and their outputs should be interpreted within an appropriate framework of professional oversight.

For the AI-enabled device, veterinary practitioners should understand the proposed function, benefits to veterinary practice, model training population, outputs, potential bias, regular system updates, and data privacy.[37,41,44] Using AI tools to make diagnostic decisions can lead to a high-risk scenario when those tools are not fully understood.[55] In general, the less human involvement in the decision-making process, the greater the risk (see examples provided by AAVSB).[37] The College of Veterinarians of Ontario (CVO) and BVA provided a list of questions to ask vendors when making purchasing decisions.[41,44] The American College of Veterinary Internal Medicine (ACVIM) AI Task Force also provided a 12 point checklist of AI validation factors to help clinicians and researchers assess AI applications.[56] Additionally, veterinarians should disclose the use of AI to clients, present alternative non-AI options, obtain

informed consent, and record the use of AI in medical records.[37–39] Ultimately, veterinarians should never assume AI outputs are accurate, and any medical decisions should be justified by their professional knowledge.[37,39,44]

ARTIFICIAL INTELLIGENCE LITERACY AND CONTINUING EDUCATION

AI currently receives relatively little emphasis in human medicine pathology training programs.[55] The same holds true for veterinary medicine. However, when it comes to decision making in adopting AI tools, veterinarians are expected to have fundamental AI literacy to ask vendors about the model testing, training, and performance.[41] Professional organizations also emphasize the importance of basic AI education for veterinary students and continuing education on AI for veterinarians in practice, with specific emphasis on the validation and evaluation of clinical performance and the risks and benefits of emerging AI technologies.[38–40,44]

Among all 31 US American Veterinary Medical Association-accredited veterinary schools, only a few offer an AI course, including the University of Wisconsin-Madison, Auburn University, Kansas State University, and Texas A&M University. The University of Wisconsin-Madison offers a 2 week rotation entitled "Artificial Intelligence for Veterinary Medicine and Life Sciences" to fourth-year veterinary students.[57] At Auburn University, the one-credit course "Spectrum of care series: emerging technology" focuses heavily on the risks, benefits, and limitations of AI applications.[58] Kansas State University has a one-credit "Artificial Intelligence in Veterinary Medicine" course that covers ML, AI applications, data science, and ethical and legal considerations.[59] Most recently, Texas A&M offers a one-credit elective course, "Artificial Intelligence and Digital Tools for Next-Generation Veterinarians," for second-year veterinary students.[60] The course covers the fundamentals of AI, ML model training and validation, introduction to large language model and prompt engineering, overview of AI policy and position statement, overview of current AI applications in veterinary research and clinical care, legal and ethical concerns, and hands-on CV exercise using cytology images and building an AI chatbot.[61] It is expected that more veterinary schools will offer AI courses as demand increases and ultimately become part of the required curriculum.

The development of AI has a significant impact on pathologists and radiologists.[62] For pathology trainees and pathologists, the Pathology Informatics Committee at ACVP has created a free-to-download "Pathology Informatics Curriculum Template and Self-Study Guide."[63] The study guide includes recommended readings and videos to build a basic understanding of CV in veterinary pathology. For veterinary radiologists, ACVR's AI page also offers AI 101 articles and videos for their specialists and trainees.[64] From a different perspective, the ACVIM also has an on-demand course named "How I Streamline Academic Writing with AI and Digital Tools" that is geared toward efficient and ethical use of AI in scientific publication.[65]

CONCERNS FOR DESKILLING AND BEING REPLACED BY ARTIFICIAL INTELLIGENCE

In addition to general issues with AI models, such as the training dataset, accuracy, bias, and safety, veterinary clinical pathologists may have concerns about deskilling. Early studies in human medicine have shown that AI assistance can improve pathologists' diagnostic accuracy in Gleason grading of prostate biopsies[66] and gastric cancer.[67] Meanwhile, it was speculated that overreliance on AI might impede the training of new human pathologists or lead to the loss of skills among experts.[55,68] A recent study in human medicine evaluated the impact of AI-generated diagnoses (with confidence scores) on pathologists' diagnostic accuracy. Bellahsen-Harrar and colleagues found that

AI-assisted pathologists had improved inter-rater reliability and a higher accuracy for laryngeal biopsies with high-grade dysplasia and invasive carcinoma. They also noted that pathologists with less experience might overrely on AI by failing to account for low confidence scores, leading to misdiagnoses. Although specialized pathologists also misdiagnosed some cases based on AI's predictions, their misdiagnoses tend to have a lower negative impact on clinical outcomes than those of their nonspecialized colleagues.[69]

Another potential concern among pathologists is the fear of being replaced by AI. In human medicine, a 2022 survey with 41 liver pathologists in the UK showed that 37% were neutral to strongly agree that AI will replace pathologists in the future.[70] In a 2025 survey of 215 cytologists in the American Society for Cytotechnology, about 25% and 14% of respondents worry that AI and digital pathology might partially or totally replace their jobs, respectively.[71] In veterinary pathology, a preliminary survey shared with attendees during the Pathology Informatics Workshop: Automated Image Analysis Using Machine Learning and the relevant AI sessions at the 2025 ACVP Annual Meeting in New Orleans suggested that concerns about outright replacement by AI were present but not predominant, with most respondents viewing AI as a tool to augment rather than replace the role of the pathologist. The same survey has been sent to ACVP members to draw a representative conclusion from the veterinary pathology community.

SUMMARY

AI has the potential to decrease turnaround time, increase diagnostic accuracy, reduce interobserver variability, and assist pathologists in repetitive tasks. These advances in human medicine will likely hold true for veterinary medicine, though the application of AI in veterinary cytology remains in its infancy. The application of CV tools in veterinary medicine faces 4 main challenges: the lack of open databases for benchmarking, the absence of centralized regulation, the lack of transparency in commercial products, and inadequate education and training. Professional organizations, such as ACVP and ASVCP, play a critical role in understanding and addressing concerns and needs of veterinary pathologists toward AI and CV. By providing official documents, including position statements, best-practice guidelines, and resident training on AI competencies, veterinary pathologists will find it easier to navigate this rapidly evolving technology.

CLINICS CARE POINTS

- AI literacy, including a basic understanding of AI and ML, is essential knowledge for both veterinary students and practicing veterinarians.
- Practitioners are encouraged to prioritize adopting AI tools accompanied by scientific publications, particularly those that follow the AI-based automated image analysis reporting guidelines.
- Critical questions to ask AI tool vendors can be found in the AI policy statements published by CVO and BVA, and the AI validation factors proposed by the ACVIM AI Task Force.

DECLARATION OF AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work the author(s) used Grammarly and ChatGPT5.2 in order to check grammar and provide word suggestions and Claude Opus 4.6 in order to generate an editable draft of Figure 1 in PowerPoint. After using this tool/service, the

author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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DISCLOSURE

The author is a member of the Advisory Board of IDEXX InVue Dx Cellular Analyzer, which employs artificial intelligence to derive diagnostic information.

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