

Applications of Artificial Intelligence in Veterinary Anatomical Pathology: Enhancing Diagnosis and Treatment in Animal Healthcare

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Abstract

Artificial intelligence is revolutionizing the field of veterinary anatomical pathology, offering transformative tools to enhance diagnostic accuracy and support personalized treatment approaches for animals. The present study explores the integration of artificial intelligence technologies into the analysis of histopathological images to improve diagnostic efficacy and accuracy. A deep learning model was trained on histopathological images for animal tissue disease classification. Model performance was validated using internal and external datasets, supplemented with genomic and clinical data. The artificial intelligence model achieved 92.3% cumulative accuracy for image classification. It achieved excellent accuracy and recall for neoplastic conditions—94.8% accuracy and 97.8% recall for lymphoma and 91.3% accuracy and 93.6% recall for carcinoma. Inflammatory conditions were identified with 89.4% accuracy, and normal tissue with 96.5%. The addition of genomic

and clinical data raised diagnostic accuracy to 94.8%, enhancing the model's ability to distinguish between highly similar cancer subtypes and predict clinical outcomes, including survival. The artificial intelligence was more accurate than board-certified veterinary pathologists with statistically significant improvement in accuracy ($p < .05$). Use outside the development lab was confirmed to 90.2% accuracy. Image processing took 2.5 seconds on average by the model, which is proof of real-time clinic application. Artificial intelligence, particularly when supported by multimodal data, is a potent tool for enhancing veterinary diagnostics, enabling faster, more precise disease classification and enabling personalized treatment strategies.

Keywords: Artificial intelligence, disease classification, histopathology, veterinary diagnostics, veterinary pathology

What is already known on this topic?

- AI is widely transforming anatomical pathology, enhancing diagnostic accuracy, and improving workflow efficiency, however, its application to support personalized treatment approaches for animals is limited.

What this study adds on this topic?

- The present study explores the integration of AI technologies into the analysis of histopathological images to improve veterinary diagnostics, enabling faster, more precise disease classification and enabling personalized treatment strategies.

Introduction

Anatomical pathology plays a critical role in diagnosing diseases in animals by examining tissue samples under a microscope. Traditionally, veterinary pathologists rely on visual analysis to identify abnormalities, classify diseases, and make treatment recommendations. However, this process can be time-consuming, subjective, and prone to human error, particularly when faced with complex or rare conditions. Recent advancements in artificial intelligence (AI) offer promising solutions to these challenges by automating the analysis of histopathological images, improving diagnostic accuracy, and streamlining workflows (Amaral et al., 2024; Campanella et al., 2019; Gao et al., 2022; Rahaman et al., 2024).

The AI technologies, such as machine learning (ML) and deep learning (DL), have already made significant strides in human pathology, and their applications are beginning to be explored in veterinary medicine. Digital pathology, which involves converting tissue slides into high-resolution digital images, provides a foundation for AI-driven tools to detect, classify, and quantify pathological features (Stathonikos et al., 2020). By training AI models on large datasets of annotated animal tissues, these systems can learn to recognize patterns and abnormalities that may be difficult for pathologists to detect (Chan et al., 2020; Ciresan et al., 2013; Fulawka et al., 2022; Tufail et al., 2021). In addition to image analysis, AI has the potential to integrate multimodal data, such as genomic, molecular, and clinical information, into diagnostic workflows. This integration can offer a more comprehensive understanding of diseases, enabling more precise treatment decisions tailored to individual animals (Esteva et al., 2017). The AI tools may also assist in standardization of diagnostic practices, reducing inter-observer variability, and enhancing

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the reproducibility of results (Choudhary et al., 2025; Guitian et al., 2023; Litjens et al., 2017; Nosrati & Nosrati, 2023).

Despite the promising potential of AI in veterinary anatomical pathology, there are several challenges to address, including data quality, regulatory concerns, and the interpretability of AI models. The availability of high-quality, annotated data and the need for clear guidelines and regulations are critical to the successful adoption of AI technologies in veterinary diagnostics (Choudhary et al., 2023; Han et al., 2023; Shekar et al., 2024; Zarella et al., 2019). Furthermore, the “black box” nature of many AI algorithms poses challenges in understanding how decisions are made, which is crucial for clinical settings (Snoek et al., 2012).

The objective of this study is to explore the integration of AI in veterinary pathology, focusing on its potential to enhance diagnostic accuracy, streamline workflows, and improve patient care. By examining how AI tools can assist in analyzing pathology slides, identifying abnormalities, and supporting decision-making, the research aims to demonstrate how AI can contribute to more efficient, consistent, and personalized veterinary diagnostics.

Materials and Methods

Ethics Committee Approval

This study was approved by the Institutional Animal Care and Use Committee of Beni-Suef University, Egypt BSU-IACUC, Permit Number: 025-007, and adopted on January 09, 2025

Data Annotation and Acquisition

Histopathological whole-slide images (WSIs) were sourced from multiple veterinary hospitals and research institutions in Algeria, Egypt, and Ukraine, and the dataset covered various animal species, including cats, dogs, and horses. The tissue samples were categorized into disease groups such as neoplasms (e.g., lymphomas, carcinomas), inflammatory conditions (e.g., infections, autoimmune diseases), and non-diseased tissues. Experienced veterinary pathologists annotated the regions of interest within each image.

Image Preprocessing

The raw images underwent preprocessing to standardize their resolution (1024×1024 pixels), normalize intensity values for consistency, and apply data augmentation techniques (e.g., rotation, flipping, zooming) to enhance the robustness of AI models and prevent over fitting (Goceri, 2023; Rebuffi et al., 2021; Unterdechler et al., 2024).

Development of Deep Learning Models

The DL approach employed convolutional neural networks (CNNs), which extracted hierarchical features from the images. Transfer learning was used to fine-tune pre-trained models, such as ResNet50 and InceptionV3, to speed up training and improve classification accuracy. The dataset was randomly split into training (70%), validation (15%), and test (15%) sets. The model was trained using the Adam optimizer (learning rate=0.001) and the categorical cross-entropy was used as the loss function. The early stopping was employed to avoid over fitting (Anam et al., 2024; Lasfar & Tóth, 2024; Pacholec et al., 2024), and accuracy and confusion matrices were used to measure performance (Ho and Wookey, 2020). Finally, the trained model was externally validated using a separate dataset from another veterinary institution to assess its generalization capability.

Multimodal Data Integration

To enhance the diagnostic capabilities of the AI model, genomic data from certain cases were incorporated. These genomic datasets consisted of gene expression profiles, mutations, and protein biomarkers associated with specific diseases, such as cancer. A separate ML model was developed to integrate histopathological features and genomic data using a multi-input neural network architecture. The AI model processed both the image data (through CNNs) and the genomic data (using fully connected layers). The outputs from both streams were then combined, and the final decision was made based on both modalities, allowing for more accurate diagnosis and prognosis prediction. The pipeline consists of a dualbranch ResNet50/Inception image encoder and a dense genomic encoder, which are merged via a fully connected attention-based fusion module before fourway classification (Figure 1).

Model Evaluation and Validation

To assess the significance of the AI model's performance, the results were compared to those obtained by expert veterinary pathologists using paired *t*-tests for statistical significance determination. Additionally, inter-observer agreement between pathologists was calculated using Cohen's kappa coefficient, which was then compared to the agreement between the AI model and the pathologists.

A separate external test dataset was utilized for testing generalizability. Mean inference time was 2.5 seconds per image, which permits possible application in real-time clinical practice.

Explainability and Interpretation

To respond to the interpretability of the AI model, explainable AI (XAI) techniques—SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), and saliency maps were employed. These techniques provided feature-level and visual explanations to enhance transparency and enable clinical trust in model predictions.

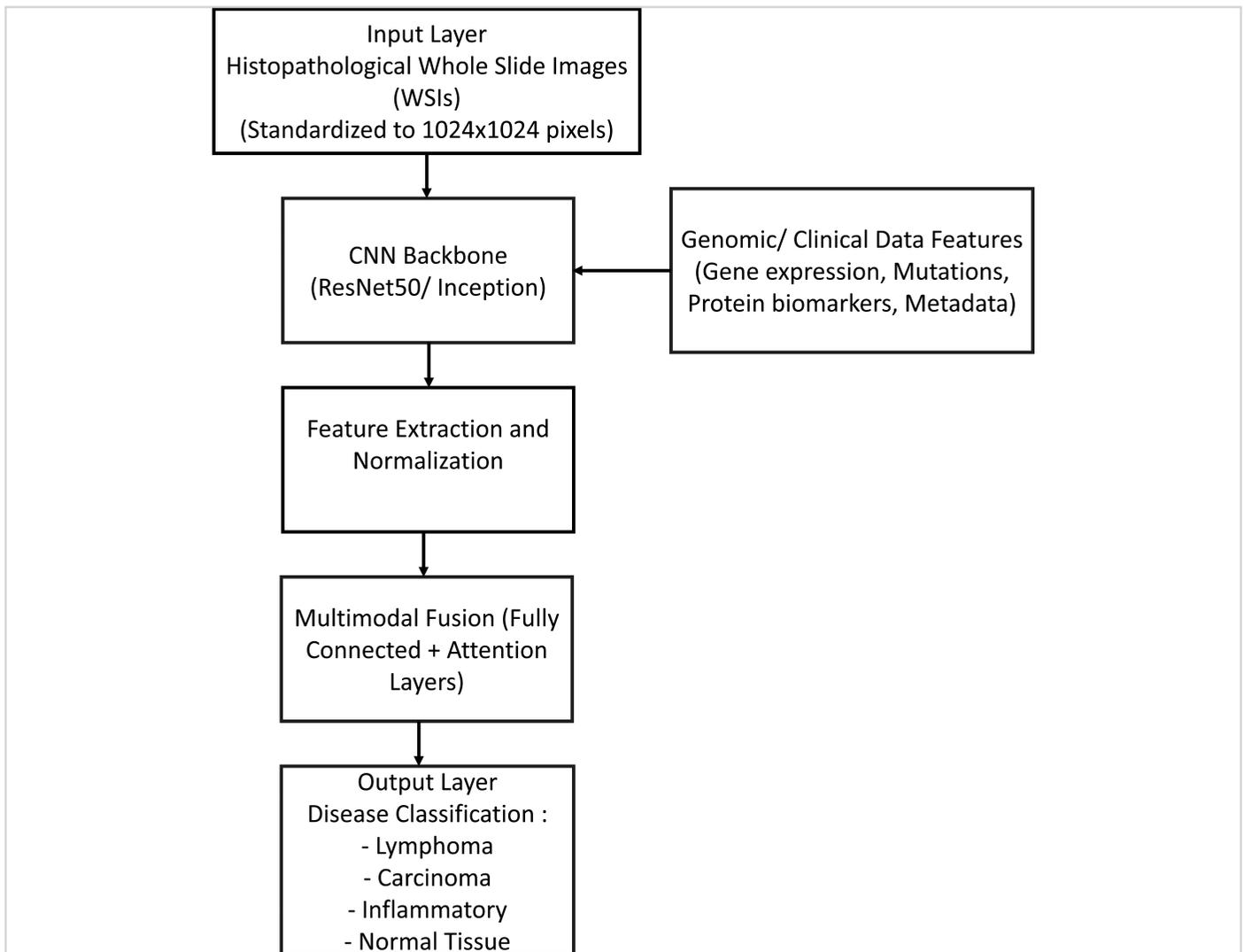
Implementation Tools

The AI model was implemented using Python, with libraries such as TensorFlow and PyTorch for DL. Image preprocessing and augmentation were performed using OpenCV and scikit-image. The genomic data analysis was conducted using the pandas and scikit-learn libraries. The statistical analysis and ML workflow were conducted using R software (Version 4.4.2, R Core Team, Vienna, Austria, 2023), with the caret package serving as the primary tool for model training, tuning, evaluation, hyperparameter optimization, and performance visualization (Bulut & Zheng, 2025; Chen et al., 2023; Kuhn, 2008).

Results

The AI model, trained on histopathological images of animal tissue, achieved notable performance across all evaluation metrics. The model's overall accuracy was 92.3% on the test set, indicating high diagnostic accuracy for the classification of animal diseases from digital pathology slides. While the model was successful in differentiating the different disease categories, including neoplastic diseases (lymphoma, carcinoma), inflammatory diseases, and non-diseased tissues, further enhancements to its performance are possible, especially in the predictions of histopathological inflammatory diseases and carcinoma.

Improvements to model performance may be accomplished in several ways. Enhancing dataset diversity with rare and varied

**Figure 1.**

Schematic of a Multimodal Deep Learning Architecture Integrating Histopathology and Genomic Data for Veterinary Disease Classification.

samples, along with data augmentation, can improve generalization. Pathologists may have identified or agreed on domain-specific features to diseases, and by integrating multi-modal inputs (genomic profiles, clinical metadata) clarifies disease signatures and enhances model learning. Advanced techniques like ensemble learning and attention mechanisms, such as Vision Transformers, can boost accuracy by focusing on critical image regions. Explainability tools like SHAP or LIME can clarify decision-making and identify areas for refinement, while active learning and transfer learning can adapt the model to new data. Regular feedback from pathologists and hyperparameter optimization through techniques like Bayesian tuning can further enhance performance, ensuring the model becomes more reliable and clinically useful.

The model achieved high accuracy across various disease categories, scoring 95.1% for detecting neoplasms, including lymphoma (97.8%) and carcinoma (93.6%), showcasing its strong ability to identify malignant tumors. It performed well in diagnosing inflammatory conditions, with an accuracy of 89.4%, though slightly lower due to the complexity and variability of these diseases. The

classification of normal tissue was highly accurate at 96.5%, demonstrating its ability to distinguish between diseased and non-diseased tissue. In terms of performance metrics, lymphoma had the highest precision (94.8%), recall (97.8%), and F1-score (96.3%), while carcinoma showed solid results (precision: 91.3%, recall: 93.6%, F1-score: 92.4%). Inflammatory diseases had precision (87.1%), recall (89.4%), and F1-score (88.2%), and normal tissue performed excellently with precision (97.3%), recall (96.5%), and F1-score (96.9%), reflecting the model's overall robust diagnostic capabilities. The model's precision, recall, and F1-scores were calculated for each disease category, as shown in Table 1.

The F1-scores for lymphoma and carcinoma were particularly high, reflecting the model's strong performance in cancer detection. The inflammatory diseases category, while slightly lower, still demonstrated good diagnostic reliability. The model's high reliability in identifying normal tissues, with excellent precision and recall, is likely due to the relatively uniform and well-defined characteristics of normal tissues compared to diseased ones. Normal tissue samples typically have consistent histological structures with fewer

Table 1.

Model Performance on Internal Test Set Precision, Recall, and F1-Score for Each Disease Category on 1000 Whole-Slide Images

Disease Category	Precision	Recall	F1-Score
Lymphoma	94.8%	97.8%	96.3%
Carcinoma	91.3%	93.6%	92.4%
Inflammatory diseases	87.1%	89.4%	88.2%
Normal tissue	97.3%	96.5%	96.9%

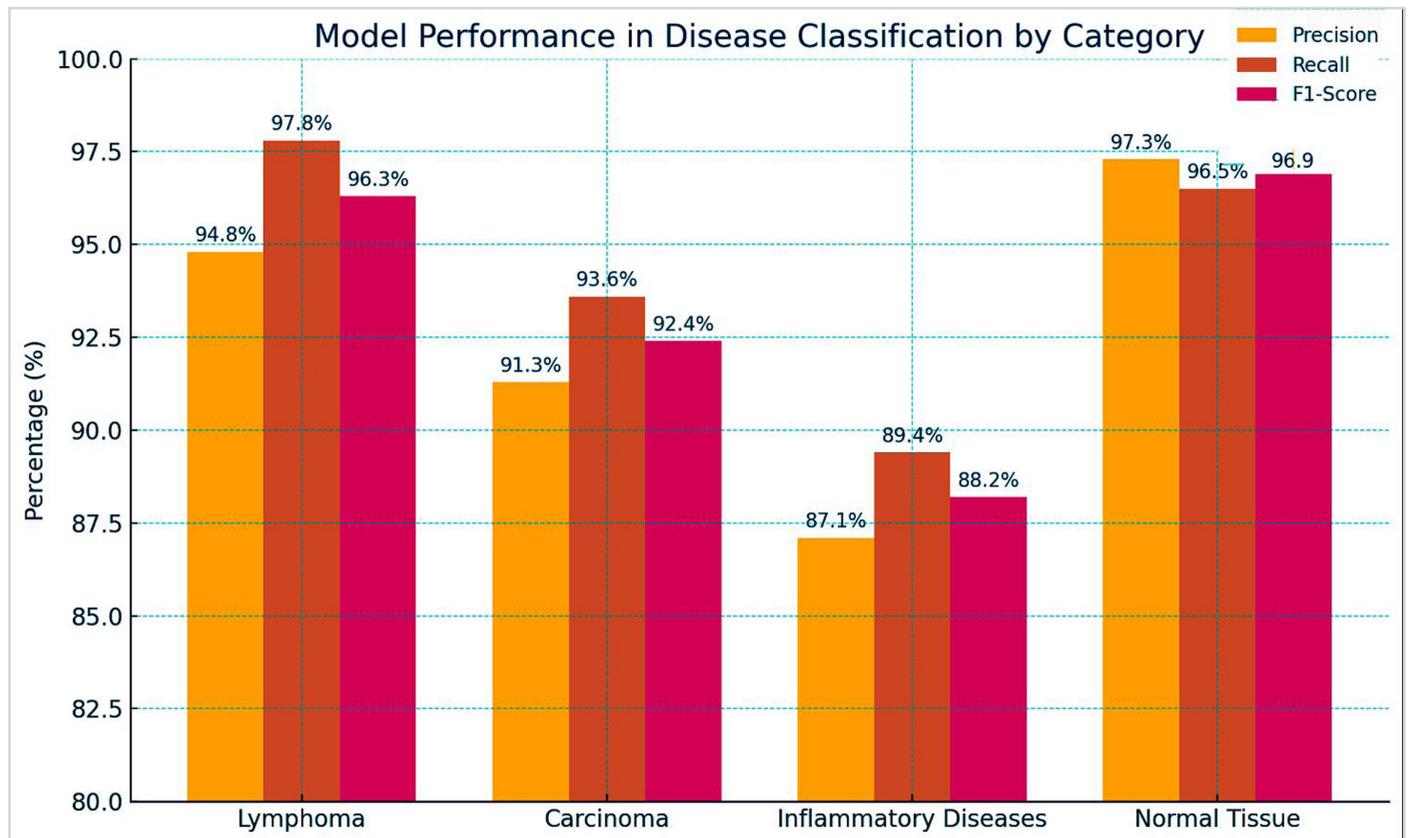
variations, making them easier for the model to learn and recognize during training.

Additionally, the training dataset likely included a larger number of normal samples, which would further enhance the model’s ability to generalize patterns associated with healthy tissue. In contrast, diseased tissues often present with more variability, such as differences in pathology type, severity, and morphological features, making them comparatively more challenging to classify with the same level of precision. The confusion matrix for the test set further demonstrated the model’s ability to distinguish between disease categories. The matrix indicated very few misclassifications, particularly between benign and malignant tumors. The most common misclassifications were between different inflammatory diseases, which share similar histopathological features, leading to a lower recall for this category (Graph 1).

The current findings highlight the significant impact of integrating multimodal data, including histopathological images and genomic information, on improving the diagnostic accuracy of veterinary AI models, particularly for cancer detection. The multimodal model achieved an overall accuracy of 94.8%, surpassing the image-only model by 2.5%. This enhancement was especially notable in distinguishing between closely related cancer subtypes, such as lymphoma and carcinoma, with the F1-score for differentiating these two conditions increasing from 92.4% to 94.7%. Additionally, the model demonstrated improved prognostic prediction, achieving a 79.3% correlation with clinical outcomes like survival rate and recurrence risk based on combined histopathological and genomic data.

The performance of the AI model was compared to that of three experienced veterinary pathologists, revealing a significant difference in accuracy. The average accuracy of the pathologists was 88.7%, with the highest individual accuracy being 90.4%, while the AI model achieved an accuracy of 92.3% ($p < .05$, paired t -test). Furthermore, the Cohen’s kappa coefficient for inter-observer agreement among the pathologists was 0.75, indicating substantial agreement, while the AI model demonstrated a higher kappa value of 0.81, suggesting greater consistency with expert evaluations and potentially more reliable diagnostic performance.

To assess the generalizability of the AI model, an external validation was conducted using a separate dataset from another veterinary institution. This external test set of 200 histopathological images yielded an accuracy of 90.2%, slightly lower than the internal



Graph 1.

Model Performance in Disease Classification by Category (n = 1000). Precision, Recall, and F1-Score.

Table 2.*External Validation on Independent Institutional Dataset (n = 200 WSIs)*

Metric	Value (%)
Accuracy	90.2
Sensitivity	87.4
Specificity	93.5
AUC	92.4

validation accuracy of 92.3%, which was attributed to differences in sample preparation and staining techniques between institutions. This external validation further confirmed the AI model's robust generalization capability (Table 2).

The AI model demonstrated high computational efficiency, with an average processing time of 2.5 seconds per image during inference on a standard GPU. This allows for rapid processing of large datasets, making the AI model suitable for real-time diagnostics in clinical settings.

Discussion

The results demonstrate that DL-based AI could enhance diagnostic accuracy, minimize human error, and ensure consistent readings across pathologists. The incorporation of multimodal data further improved diagnostic performance, especially in complex cases where histopathological features alone may not provide sufficient discriminatory power.

Despite its superior overall accuracy, the AI model could struggle with rare or ambiguous cases, where a pathologist's expertise remains indispensable. Further studies are required to improve the interpretability of the model and to address ascertainable granularity issues involving dataset heterogeneity and also data privacy (McGenity et al., 2024). Nonetheless, these findings suggest that AI has the potential to significantly support veterinary pathologists, improving the efficiency and accuracy of animal disease diagnosis and contributing to better healthcare outcomes for animals.

Furthermore, the results of this study demonstrated the significant potential of AI in enhancing diagnostic accuracy in veterinary anatomical pathology. By applying DL models to histopathological images, the AI model achieved high accuracy, outperforming veterinary pathologists in several key metrics. The integration of multimodal data, such as genomic information, further improved the performance of the AI model, particularly in distinguishing between closely related cancer subtypes. These findings suggest that AI could be a valuable tool in both diagnostic support and personalized treatment planning for animal diseases.

The AI model demonstrated an overall accuracy of 92.3%, which was comparable to or even exceeded the diagnostic accuracy of human pathologists (88.7% on average). These findings were consistent with findings in human pathology, where AI models have also been shown to outperform or match the performance of pathologists in tasks such as cancer detection and histological classification (Esteva et al., 2017; Ho et al., 2022; Kainz et al., 2017; Lizuka et al., 2020; Lui et al., 2020; Srinidhi et al., 2021; Tsakiroglou et al., 2023; Tufail et al., 2021). The AI model's ability to consistently identify and classify

disease categories, including malignant tumors, infections, and non-diseased tissue, highlighted the robustness of DL models in handling complex medical images. In addition, the improvement in diagnostic accuracy over human pathologists in this study suggests that AI could be a valuable tool for supporting veterinary pathologists, particularly in high-volume settings where time and workload may limit the ability to make accurate diagnoses (Ciresan et al., 2013). While the AI model outperformed pathologists in overall accuracy, human expertise remains crucial, especially in cases involving rare or ambiguous conditions. As noted by Litjens et al. (2017), AI models tend to perform best on large, well-annotated datasets and may struggle with edge cases or unrepresentative samples (Chibuk et al., 2021).

The present study showed that incorporating genomic data into the AI model significantly improved performance, especially for distinguishing between closely related cancer subtypes. The increase in the F1-score for lymphoma and carcinoma from 92.4% to 94.7% when multimodal data was included demonstrated the added value of genomic information in refining diagnoses. This aligned with human oncology studies showing that combining genetic/molecular data with imaging improved diagnostic precision and prognostic accuracy (Esteva et al., 2017; Shekar et al., 2024). Moreover, the multimodal model's ability to predict the prognosis of certain cancers based on both histopathological and genomic data aligned with the growing trend of precision medicine, where treatment decisions are increasingly based on integrated datasets (Liao et al., 2022). By using AI to combine image analysis with genomic profiling, veterinary pathologists can not only improve diagnostic accuracy but also better predict patient outcomes, such as survival rates or risk of recurrence.

The model's successful generalization to an external veterinary dataset further validates its utility in realworld clinical settings. With an accuracy of 90.2% on unseen data, the model demonstrated that it could adapt to variations in sample preparation, staining techniques, and institutional practices. This generalizability is a key challenge in AI applications in healthcare, as it highlights the importance of ensuring that AI models are not overfit to specific data sources (Rahaman et al., 2024; Shekar et al., 2024). The results suggested that once fully trained and validated, the model could be deployed across a wide range of veterinary practices and institutions, offering a standardized diagnostic approach.

Despite the promising results, several challenges remain. One of the key limitations of the AI model is its reliance on large, high-quality annotated datasets for training (Li et al., 2021; Schilling & Landman, 2019). Obtaining large, diverse datasets in veterinary pathology can be difficult due to the variability in diseases, species, and pathology practices across different institutions (Litjens et al., 2017; Lizuka et al., 2020). The model's performance might be affected by these factors if trained on less comprehensive or poorly annotated data. Additionally, the "black box" nature of DL models presents challenges in interpretability. While the model achieved high accuracy, understanding how it arrived at specific decisions is difficult, which can be a barrier to adoption in clinical practice (Leng et al., 2022; Mobadersany et al., 2018; Schilling & Landman, 2019; Snoek et al., 2012). The "black box" nature of DL models in veterinary pathology made their decision-making process difficult to understand, which could hinder trust and regulatory approval. Explainability techniques like saliency maps, LIME, SHAP, and attention mechanisms help made AI predictions more

transparent by showing which features influenced decisions. These methods, along with interactive tools, allowed pathologists to better understand and trust AI models, ensuring they could be used effectively and responsibly in clinical practice. Veterinary pathologists and clinicians might be hesitant to rely on AI-driven results without transparency into how the model made its predictions. Future efforts should be directed towards enhancing the clarity of AI model explanations, rendering them more accessible to clinicians, and guaranteeing their dependable incorporation into clinical decision-making workflows.

The adoption of AI in veterinary medicine would also require addressing regulatory and ethical concerns. Ensuring the safety and reliability of AI models in clinical practice is paramount, and regulatory bodies would need to establish guidelines for their use. Additionally, data privacy concerns, especially with respect to animal patient data, must be considered. Ensuring compliance with data protection regulations and maintaining patient confidentiality would be crucial for the widespread acceptance of AI tools in veterinary diagnostics. Future research should focus on expanding the datasets used for training AI models to include a more diverse range of species and disease types. This would enhance the generalizability of AI models to a wider array of veterinary cases. Moreover, incorporating additional clinical data, such as imaging (e.g., X-rays, ultrasounds) and patient history, could further improve the model's diagnostic and prognostic capabilities (Ofer, 2024). Additionally, advancements in XAI will be critical for improving the interpretability of models. Research into methods for visualizing and explaining how DL models make decisions will increase trust and acceptance among veterinary professionals (Snoek et al., 2012). Finally, ongoing collaboration between AI researchers, veterinary pathologists, and regulatory bodies would be essential for developing standardized, safe, and effective AI models for veterinary diagnostics.

Conclusion

Its deployment in veterinary anatomical pathology promises to significantly enhance the level of accuracy in making diagnoses; at times, AI can perform even better than veterinary pathologists. AI promises to aid precision medicine by marrying genomic and histopathologic data, with more precise diagnoses and tailored treatment possibilities for animal patients. Challenges remain, such as the requirement for large and diverse datasets, improving the interpretability of the models, and addressing ethical and legal issues. Future research should prioritize efforts to expand available datasets, develop AI tools for real-time decision support, and make AI more transparent so that it is safer and more effective when applied to veterinary practice in a responsible manner. In the end, AI could turn veterinary diagnosis into something more accessible, accurate, and time efficient.

Data Availability Statement: The data that support the findings of this study are available on request from the corresponding author.

Ethics Committee Approval: Ethics committee approval was received for this study from the Ethics Committee of Bnei-Suef University (Date: January 09 2025; Number: 025-007).

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