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Revolutionizing Pathology in the Philippines: Artificial Intelligence in Digital Image Analysis

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ABSTRACT

Artificial Intelligence (AI) is transforming the landscape of pathology, particularly in resource-constrained settings like the Philippines. This narrative review explores the applications, challenges and future potential of AI in digital image analysis for pathology practices. By synthesizing peer-reviewed literature from 2019 to 2025, the review highlights the role of machine learning (ML) and deep learning (DL) algorithms in enhancing diagnostic accuracy, workflow efficiency and clinical decision-making. AI-driven tools such as convolutional neural networks (CNNs) and transfer learning models have demonstrated significant success in tumor detection, biomarker evaluation and predictive analytics, paving the way for personalized medicine. However, barriers such as limited annotated datasets, privacy concerns and model interpretability hinder widespread adoption. The review emphasizes the need for ethical frameworks, workforce training and infrastructure development to ensure equitable and effective integration of AI into pathology practices. By addressing these challenges, AI has the potential to improve diagnostic precision, expand access to healthcare and modernize pathology services in the Philippines.

Key words: artificial intelligence, pathology, digital image analysis, Philippines, deep learning, machine learning, diagnostic assistance

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INTRODUCTION

The field of pathology research is changing rapidly because of artificial intelligence (AI), especially in terms of research approaches, diagnostic procedures and educational instruction. AI-enhanced computers can now do tasks that once required cumbersome manual methods; for example, they can recognize images, analyze data and speed up diagnostics in pathology and arguably surpass traditional methods in certain workflows.[1]

The COVID-19 pandemic has fast-tracked the development and use of digital pathology by offering the opportunity for remote, end-to-end digitization of histopathological workflows. The design of a new remote workflow illustrates the importance of AI in the delivery of clinical services to safeguard their continuity, resilience and to support the longer-term development of telepathology in the face of extraordinary circumstances.[1]

Machine learning (ML) and deep learning (DL), which are core components of AI, enable systems to improve their output through feedback mechanisms and iteration without the need for a rule-based system that is explicitly programmed. DL employs multilayered artificial neural networks to extract and distinguish complex, nonlinear, and/or high dimension data patterns. These methods have been extremely successful in histopathology in terms of extracting features from whole-slide images, detecting abnormalities, and automating aspects of image classification, allowing for consistent, rapid, reliable, and reproducible results that improve the sensitivity and specificity of diagnostic interpretations.[2]

AI algorithms have achieved impressive results in a wide range of clinical domains, including diagnosing ophthalmic diseases, detecting oncogenic gene fusions in lung cancers, and identifying disease-specific biomarkers for precision medicine. Furthermore, one branch of AI known as computer vision allows for automated whole-slide image analysis, which significantly reduces turnaround time for pathology cases while also assisting pathologists with interpretative and diagnostic decision-making.[3]

Apprehensions by pathologists are expected but understandable and need to be addressed appropriately. To facilitate successful technology acceptance, it must be emphasized that pathologists will not be replaced through AI implementation, as its primary purpose is to enhance and not substitute for their professional functions.[4] The combination of artificial intelligence pattern recognition abilities and human professional knowledge, the so-called "human in the loop" strategy, results in improved diagnostic accuracy, especially during challenging or uncommon treatment scenarios.[5,6] This paradigm and the broader concept of "group intelligence" model, creates exciting opportunities for health care innovation.[7]

As the world of artificial intelligence develops, its acceptance and use in healthcare delivery and biomedical education and training are vital. Preparing the practitioners of the future with competency in the use of artificial intelligence tools will support the routine implementation of artificial intelligence in pathology practices.[8,9] Together, advances in artificial intelligence technologies and expert human judgment will shape the future of the pathology practice environment, enhancing diagnostic accuracy and ultimately, patient outcomes.

Although there has been a lot of progress in this area, the real-world use of artificial intelligence in pathology is still a major hurdle. The main worries are various factors, such as the performance differences of convolutional neural networks (CNNs) at different hospitals and among different patient groups, and the very existence of imaging protocols that are not standardized, as well as the risk of using flawed or non-inclusive training datasets, all of which are pointed out in recent studies regarding CNN-based classification of brain tumors.[10] Xie et al., concluded that numerous top-notch models depend on small, well-defined datasets and thus are prone to issues of non-generality, non-interpretation, and non-reproducibility when applied to real-world clinical settings. Ethical issues like openness, model interpretability, and accountability to the public make it even harder to lay down a process, while medical personnel's reluctance about relying on machines continues to be a roadblock to the embracing of automated systems. These difficulties bring into sharp focus the need for a hybrid, clinician-centered approach that effectively marries technology's latest breakthroughs with the everyday practicalities of clinical pathology.[10]

The principal aim of this manuscript is to explore the transformative role of artificial intelligence in pathology while critically exploring the barriers to widespread integration, in particular, foreshadowing how AI supports research, diagnosis and education in pathology, to discuss its role in the COVID-19 pandemic and to suggest best practice strategies for uptake including the use of a "human in the loop" approach. The manuscript aims to clarify the opportunities and constraints in this domain with the aim of informing practice, policy and future research in digital pathology.

METHODOLOGY

Literature search strategy

This narrative review compiled peer-reviewed literature on artificial intelligence (AI) in a digital image analysis seen in some pathology practices in the Philippines. A systematic electronic search was carried out using PubMed, Scopus, IEEE Xplore and Google Scholar, from January 2019 until August 2025. The search strategy consisted of combinations of keywords and Boolean operators, ("artificial intelligence" OR "machine learning" OR "deep learning" OR "digital pathology") AND ("Philippines" OR "Southeast Asia") AND ("image analysis" OR "histopathology"). Title/abstract title screening and full-text review were completed by two independent reviewers. These reviewers reconciled discrepancies by consensus or with a third reviewer. The reviewers limited their considerations to studies published in English that focused on studying diagnostic performance (e.g., sensitivity, specificity, accuracy) of AI models used in pathology.

Inclusion and exclusion criteria

Studies were included if they focused on the application of artificial intelligence (AI) in pathology, particularly in digital image analysis, clinical diagnostics, or machine learning (ML) methods for histopathology. Eligible studies emphasize diagnostic accuracy, workflow efficiency and/or contributions to personalized medicine.

Studies were excluded if they (a) examined AI applications outside the field of pathology, (b) discussed general medical AI without a focus on digital imaging or histopathology, (c) employed outdated methodologies or lacked sufficient methodological rigor, or (d) overlapped with inclusion criteria but did not report measurable outcomes related to diagnostic accuracy, clinical utility, or workflow improvements. Studies with insufficient data, non-peer-reviewed reports, or conference abstracts without full-text availability were also excluded.

Risk of bias assessment

The QUADAS-2 tool was employed to assess the methodological quality of the included studies on diagnostic accuracy. The evaluation was performed based on four major domains, namely, patient selection, index test, reference standard, and flow and timing. In general, a good number of studies showed a low risk of bias in their index test and reference standard domains, especially those that used deep learning architectures for cancer prognosis, tumor detection, and image classification, which is in line with the methodological strengths recognized in RNA-seq-based survival prediction models by Huang et al.[11] On the other hand, there were issues in the selection of patients, since some of the studies depended on data from single centers or retrospectives datasets which made the results less generalizable. Furthermore, flow and timing bias were noted in the studies that did not clarify whether index test interpretations were not influenced by the reference standards, thus raising the risk of information leakage. Several models reported high diagnostic and prognostic

Table 1. Comparison of Machine Learning and Deep Learning AI

Aspect	Machine Learning (ML)	Deep Learning (DL)
Model types	Decision Trees, SVMs, Ensemble Methods	CNNs, RNNs, Transformers
Feature extraction	Manual Feature Engineering	Automatic Feature Extraction
Data requirements	Smaller datasets can be effective	Requires large datasets for training
Interpretability	Generally more interpretable	Often considered a "black box"
Applications	Classification of structured data	Image classification, segmentation, detection

performance levels, comparable to that of expert assessment, however, their reliance on curated, homogeneous datasets and lack of external validation raised applicability issues. These phenomena similar to the limitations pointed out by Huang et al.,[11] which call for the employment of more varied datasets and rigorous validation as a means to boost confidence in AI-assisted diagnostic tools.

Taken together, while most included studies reported promising accuracy, efficiency, and workflow improvements, the risk of bias analysis highlights the need for larger, multi-institutional studies with transparent reporting, external validation and improved dataset diversity. These measures would reduce bias and strengthen confidence in the clinical translation of AI applications in pathology.

Data extraction and thematic analysis

The following information were extracted from each of the studies: author, year, AI model used, dataset size, pathology domain, outcome metrics and key findings. Studies were categorized and synthesized by AI technique: traditional machine learning (ML), deep learning (DL) and explainable AI (XAI).

Given methodological heterogeneity, including variations in algorithm types, model architectures, data sources and clinical endpoint, results were summarized narratively rather than pooled quantitatively. ML models such as support vector machines (SVM) and decision trees were contrasted with convolutional neural networks (CNNs) and transfer learning strategies in DL. Similarly, XAI approaches like LIME and SHAP were explored for their roles in enhancing model interpretability. These groupings allowed for thematic synthesis based on functionality, assumptions and applicability in resource-constrained healthcare systems such as those in the Philippines.

Key themes analyzed

The following key themes were analyzed:

1. AI techniques and algorithms in pathology
2. AI applications in pathology
3. Workflow optimization
4. Challenges and limitations
5. Validation and clinical implementation
6. Future directions in AI-driven pathology

Critical evaluation and discussion

Qualitative synthesis identified patterns, knowledge gaps and comparative insights. AI's impact on diagnostic accuracy and efficiency was assessed through global comparisons and potential applications in the Philippines. Ethical concerns, implementation barriers and future possibilities were examined.

RESULTS AND DICUSSION

The following section presents findings clustered according to thematic discussions. While structured searches of the literature informed this synthesis, it does not meet the methodological standards of a systematic review as defined by PRISMA 2020 guidelines. As such, this review should be interpreted as an integrative narrative overview rather than a formal systematic analysis.

Foundations of AI in pathology: ML, DL and XAI

Comparative performance of ML and DL techniques

Machine learning (ML) and deep learning (DL) continue to refine pathology diagnostics, with advancements in transfer learning and explainable AI (XAI) further enhancing precision and efficiency. As shown in Table 1, ML and DL differ in model architecture, feature extraction strategies, data requirements and interpretability, yet both support increasingly sophisticated diagnostic applications. ML enables systems to learn from data patterns and make predictions without explicit programming. DL, a specialized branch of ML, uses layered neural networks to analyze complex data such as medical images.

ML algorithms like decision trees and support vector machines (SVMs) support clinical decisions by organizing data into structured decision pathways and identifying patterns in high-dimensional space. Ensemble models like random forests and gradient boosting combine algorithms to produce more stable and precise diagnostic tools.[11]

DL models, particularly convolutional neural networks (CNNs), have transformed medical image analysis by extracting image features automatically. CNNs have demonstrated high accuracy in brain tumor detection using MRIs.[12] Recurrent neural networks (RNNs) manage sequential clinical data to predict disease progression,[13] while transformer architectures, originally developed for language processing, now enhance image analysis by learning long-range relationships.[14]

Transfer learning using pre-trained models such as VGG and ResNet improves training efficiency and performance, especially with limited datasets.[15] These methods have proven successful in melanoma diagnostics.[16] Tools like LIME and SHAP contribute to XAI by making AI model decisions interpretable, supporting clinician understanding and building trust.[17]

Applications in Diagnostics and Clinical Workflows

Applications and technical enhancements of AI in pathology

AI enhances digital pathology through applications in diagnostic support, tumor detection, image classification, biomarker quantification and predictive analytics.[18] AI improves the analysis of whole slide images (WSIs), supporting faster and more accurate diagnoses.[19] In urologic pathology and oncology, AI assists in histopathological analysis, helping tailor treatment strategies.[20-22]

In prostate cancer diagnosis, AI systems have demonstrated expert-level grading accuracy, thereby supporting standardized histological classification.[23,24] For instance, Trabelsi et al.,[25] demonstrated that AI-driven classification frameworks applied to PET/CT imaging improved the precision and consistency of tumor staging in lung cancer, reducing variability that often arises from manual interpretation. Similarly, Han[26] highlighted how AI systems in brain tumor recognition can enhance diagnostic reliability by minimizing human error and addressing inconsistencies in expert assessments. Together, these findings underscore how AI not only strengthens diagnostic accuracy but also improves workflow efficiency by supporting faster, more standardized review processes across large volumes of clinical imaging data.

Beyond prostate pathology, AI applications have also been extended to pediatrics and other malignancies. Kamp et al.,[27] evaluated AI-based histopathology models in Wilms tumor diagnosis, demonstrating comparable accuracy to human experts in differentiating tumor subtypes. However, the study noted that performance was influenced by the size of the training dataset, pointing to a limitation in generalizability when data are scarce. Similarly, AI-driven methods for quantifying protein expression in immunohistochemistry (IHC) have been shown to improve reproducibility in biomarker assessment, supporting more consistent treatment planning.[28] These workflow enhancements reduce inter-observer variability and shorten turnaround time, which are critical to clinical efficiency.

Huang et al.,[29] extended this application to MRI-based monitoring of disease progression, demonstrating how AI can aid longitudinal tracking of tumor dynamics. While promising, these radiology-focused studies often rely on retrospective datasets, raising questions about real-world applicability in diverse patient populations.[30]

Predictive modeling also enhances the functionality of AI in clinical decision-making. Keim-Malpass et al.,[30] and Rana and Shuford[31] examined outcome prediction models in the context of oncology and demonstrated improved capability in predicting disease trajectories with timely intervention strategies. These predictive abilities, when merged with pathology workflows, can serve to connect diagnostics knowledge with individualized treatment plans.

Enhancing workflow efficiency and quality control

AI enables workflow efficiency and quality control in pathology by improving aspects such as image segmentation, slide quality assessment and automatic specimen worry; just to name a few. Convolutional neural networks (CNN) have been applied in histopathology (or other pathology applications) for anatomical segmentation with great accuracy.[32] In one study, CNNs that achieved a Dice coefficient of 73%, when segmenting slides for pancreatic ductal adenocarcinoma, meaning a substantial overlap of automatic segmentation with expert annotations. The study utilized digitized pathology images from many clinical cases and showed that automated segmentation saves pathologists time and effort, while providing fixed and reproducible edges. The authors did admit to shortcomings in external validity, attempting to use a model with slides from institutions with different stain protocols had potentially reduced accuracy as it portrayed a challenge to cross-site generalizability.[33]

AI systems are also being utilized to improve quality control in pathology workflows. Automated algorithms can screen and flag low-quality or artifact-heavy slides that could compromise diagnostic interpretation.[34] This contributes to efficiency by ensuring that pathologists focus only on diagnostically usable material and minimizes delays caused by repeat slide preparation. Such quality control mechanisms support laboratory standardization, reduce variability across technicians and create a more robust diagnostic pipeline.

Another critical factor in developing effective AI models is the availability of annotated datasets. Since manual annotation by expert pathologists is labor-intensive, researchers have explored alternative approaches. Selnes et al.,[35] for instance, evaluated a semi-supervised learning model for gastrointestinal polyp detection in endoscopic images. Their study demonstrated that the model achieved high sensitivity and specificity even when trained on a relatively small manually labeled dataset, thereby reducing the annotation burden. While promising, the study acknowledged that performance may vary when applied to rare or atypical polyp morphologies, suggesting that broader validation is required before clinical deployment.

Finally, AI-driven triaging systems have shown potential in optimizing hospital resource allocation and prioritizing urgent cases.[36,37] By automatically categorizing specimens according to risk profiles, these systems accelerate review of high-priority slides, enabling earlier interventions and improving patient care efficiency. Although current evidence is largely based on retrospective validation studies, the results suggest that AI-based triaging can significantly streamline diagnostic workflows, reduce turnaround times and improve alignment of resources with patient needs.

Ethical, technical and implementation challenges

Challenges and barriers to AI adoption in pathology

AI adoption in pathology encounters several significant challenges spanning data, ethics and practical implementation.[38] A primary technical barrier is the scarcity of large, diverse and well-annotated datasets critical for effective AI training.[39] Developing these datasets involves substantial financial investment, raises patient privacy concerns and requires considerable pathologist time for manual annotation.[40] Eloy et al.,[41] conducted a systems-based review of data management in pathology laboratories, demonstrating that structured digital archiving and efficient data pipelines can improve processing speed without sacrificing diagnostic quality. However, they highlighted that most datasets remain limited in scope, typically sourced from single institutions or specific populations, which restricts the external validity of AI models. Supporting these findings, Berbís et al.,[42] identified a "translation gap" in their multicenter analysis showing that models trained on narrowly defined datasets performed well locally but exhibited reduced accuracy when applied to data from different geographic or clinical settings. Their study underscored the promise of federated learning and international data-sharing initiatives to enhance generalizability, despite ongoing legal and ethical hurdles.

Clinical integration and workforce readiness

Ethical difficulties also have a heavy burden on the role of AI in Pathology. Interpretability of AI models has been identified as an important issue regarding clinician acceptance. Clinicians do not favor trusting "black box" systems that do not make clear how predictions were made, which can foster distrust of AI models. Montezuma et al.,[43] carried out a survey of practicing pathologists working in academic institutions, with over 60% of respondents unwilling to rely on AI tools that did not provide a defined decision pathway. They made a call for the development of explainable AI systems, but they recognized that there are trade-offs in explaining how the AI model made a particular prediction versus computational power. Dow et al.,[44] examined existing guidelines from institutions in North America and Europe and summarized that ethical scrutiny and regulatory guidance related to pathology AI model use were considerably behind other areas of technology. The absence of policies means a lack of accountability and limits the potential rate of adoption of AI in clinical practice, especially in low-resource contexts.

Benchmarking AI tools through comparative metrics

Integrating AI into pathology workflows raises additional issues related to validation, clinician acceptance and workforce readiness. For example, Hanna et al.,[45] performed a validation study using cross-validation and external datasets ultimately finding high diagnostic reliability when trained on a diverse dataset with diverse training variants; however, accuracy decreased markedly for rare tumor subtypes, highlighting the importance of continual validation across pathology domains. Zarella et al.,[46] studied experiences from pilots for AI implementations in clinical pathways, highlighting the positive impact on turnaround time and improved accuracy across AI-based pathology systems across clinical pathology. However, many clinicians were cautious and indicated that they would wait for large prospective studies before adopting the technology.

Scalability and evidence-based implementation in the Philippine context

To provide further context to these findings, Huo et al.,[47] systematically examined the integration of AI in a hospital network and concluded that AI adoption was determined by AI model quality but more importantly by sufficiently training staff and changing their workflows. In their mixed methods study, Huo et al., reported that not being adequately trained was a major barrier to integration, although results were limited to a single region. It appears that in addition to the studies previously presented, all these studies suggest that effective AI adoption in pathology relies on strong validation, reasonable integration plans and workforce development.

AI implementation in pathology flow diagram

The flow chart (Figure 1) provides a framework for understanding the process of AI implementation in pathology. At the center is an AI model that can be implemented in three contexts: challenges and barriers, clinical implementation and validation or benchmarking. The challenges and barriers, namely ethical, technical and practical issues, need to be accounted for in the pathway to adoption. The bottom of the flow chart displays scalability in the Philippine context as the final output but only supported by the former issues and the workflow characteristics. The arrows emphasize that the emergence from these barriers, clinician readiness and validation of AI tools are interdependent processes that will determine whether AI can be successfully scaled and sustainably implemented into local pathology workflows.

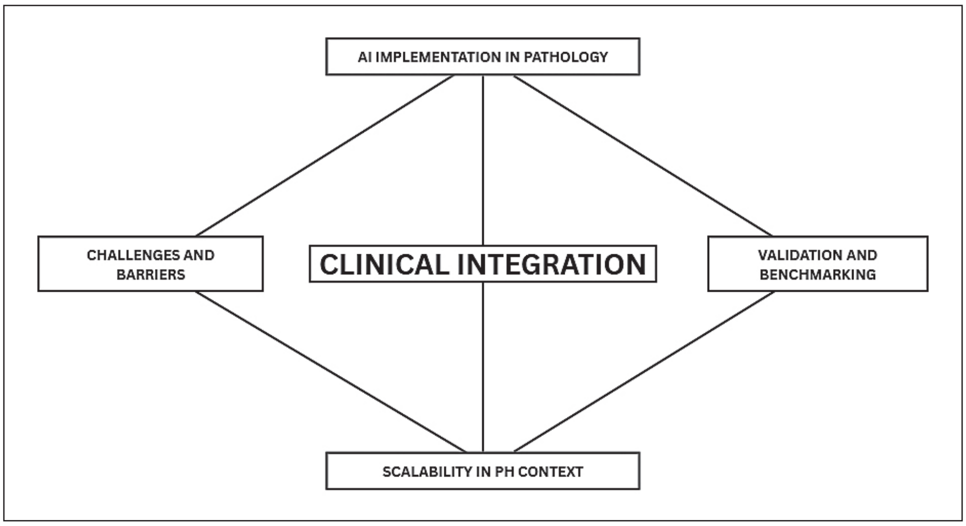

Figure 1. Framework for clinical integration of AI in pathology.

Future directions and innovations

AI in pathology must remain a supporting technology that supplements the capabilities of pathologists with its diagnostic capabilities, not displace them as the final decision-maker. An effective AI could improve both the speed and accuracy of diagnosis, while providing a human expert with a valuable tool to manage complex image analysis. In this way, we maintain human decision making but improve human oversight in decision-making, improving our ability to serve clinical responsibility and ultimately the patient. The regulatory oversight from the Department of Health (DOH) and Food & Drug Administration (FDA) on the AI development process put the care back into healthcare and ensure we can safely develop and utilize these technologies in a healthcare context.[48]

As we move forward, there is hope for new technological innovations with generative AI and self-supervised learning to solve the problem of limited labeled data in medical imaging. Generative AI will allow advances in the field without the notable burden of needing annotated datasets, which can be timely and expensive to put together, ultimately allowing safe and rapid development of a more robust AI model. For example, Yao et al.,[49] have been able to create new sophisticated algorithms that can detect subtle features of an image that an observer (a human) may miss or not even see, thus allowing enough insight for more individualized and specific management for the patient. These technologies are just a couple examples of the ways in which AI can augment healthcare solutions and importantly create unique and meaningful diagnostic insight.

In addition, using AI technology live during clinical work has the potential to provide pathologists with immediate diagnostic assistance, improving the decisions they can make in real time. Andreychenko et al.,[50] describe real-time AI image analysis using objective diagnostic support that is relevant to workflows and could increase diagnostic productivity in busy clinical practice. Certainly, there are promising opportunities for AI to improve equity in healthcare through diagnostics in settings with fewer resources. Chatrian et al.,[51] provided one example of connecting rural healthcare providers via AI-powered digital platform to receive expert-level pathology diagnosis remotely, which could facilitate high-quality diagnostic services to places with poorer access to specialist care.

These possibilities and directions offered by AI suggest a continued emergence of advanced computational approaches alongside clinical practice. We hope to use these together to improve clinical accuracy, enable smarter workflows and supply more equitable access to care, all with the supervision of a human pathologist.

Comparative performance of ML and DL techniques

Conventional machine learning (ML) methods such as decision trees and support vector machines (SVMs) have become popular due to their efficiency and an emphasis on human interpretability. In contrast, deep learning (DL)/convolutional neural networks (CNNs) methods, for example, VGG and ResNet, are more adept at processing nonlinear problems on high-dimensional and complex data such as medical images.

In the end, it is up to the user or researcher to determine the best technique to utilize. Interpretability is still a major factor in the decision-making. Machine Learning (ML) methods can be made interpretable by means of the employment of specialized software tools like LIME and SHAP which reveal the involvement of different model features throughout the modeling and prediction processes (thus creating some visibility and transparency on the influence of certain features on the model predictions). Deep Learning (DL) models have the issue of non-interpretability; nonetheless, there have been recent efforts applying LIME and SHAP to convolutional neural network (CNN) outputs that are still far from being on par with ML methods as far as explanation is concerned and have not been developed for the health sciences and medical imaging areas.

Ultimately, the decision to use ML or DL techniques depends on multiple factors: data availability, task complexity and resource constraints. For simpler tasks with structured data and limited samples, traditional ML approaches provide a reliable and interpretable solution. However, for more complex tasks involving large volumes of unstructured image data, DL methods exhibit superior performance despite higher computational demands. This trade-off is exemplified in the reviewed studies, which consistently show ML's advantage in speed and straightforward interpretation and DL's strength in accuracy and handling data complexity.

Applications and technical enhancements of AI in pathology

AI applications within pathology can be broadly categorized into predictive analytics, tumor detection, digital image analysis and immunohistochemical quantification. Advances in the use of deep learning data-driven algorithms for evaluating biomarkers have refined each stage of clinical decision-making in a personalized way. AI-based predictive models help in forecasting disease progression and treatment response, increasing the overall ability to deliver more proactive and personalized healthcare to patients. AI helps to minimize human error in diagnostics and thus optimizes workflow for diagnostic pathology to improve the practice of precision medicine and clinical outcomes.

Another area of AI use seeks to improve automation of tasks related to slide segmentation, quality control and case prioritization. Accurate segmentation and removal of low-quality suboptimal slides can maximize the reliability and speed of diagnosis. Automated data annotation can expedite the model training process, while AI-based case triage can direct clinician attention to those cases that require urgent or immediate management.

Challenges and barriers to AI adoption in pathology

However, even with those considerations, there are several challenges to consider regarding AI adoption in pathology. The challenges are to acquire sufficient high-quality labeled data sets, data privacy considerations and labeling and generalizability issues. Low data quality diminishes the reliability of the diagnostic, while privacy issues introduce ethical issues particularly when dealing with patient cases that are sensitive. In addition, when there are often very diverse demographic populations accommodating them, it

Table 2. Summary of AI applications in digital pathology (2019-2025)

Study (year)	Disease area / task	Sample size / dataset	AI model type	Performance metrics	Validation method
McGenity et al. (2024)	Various diseases (WSI-based diagnosis)	152,000+ WSIs across 100 studies	Various AI models (systematic review)	Sensitivity: 96.3% (95% CI: 94.1–97.7); Specificity: 93.3% (95% CI: 90.5–95.4)	Meta-analysis of 48 studies
Vorontsov et al. (2019)	Pan-cancer detection across 17 types	1.5 million WSIs	Vision Transformer (Virchow)	AUC: 0.949 (overall); AUC: 0.937 (7 rare cancers)	Internal and external validation
Talo (2019)	Histopathology image classification	Public datasets (24 categories)	DenseNet-161, ResNet-50	Accuracy: 97.89% (DenseNet-161); 98.87% (ResNet-50)	Cross-validation
Alom et al. (2023)	Multiple tasks (e.g., IDC detection, segmentation)	Public datasets (various tasks)	Advanced DCNNs (e.g., IRRCNN, DCRCN)	High performance across tasks (e.g., sensitivity, specificity, F1-score)	Task-specific evaluations
Allen et al. (2025)	HER2 status evaluation in breast cancer	~1,100 samples	10 AI tools compared	High agreement with expert pathologists; variability at low expression levels	Comparative study across tools

WSI: Whole Slide Image
AUC: Area Under the Receiver Operating Characteristic Curve
DCNN: Deep Convolutional Neural Network
IRRCNN: Inception Residual Recurrent Convolutional Neural Network
DCRCN: Densely Connected Recurrent Convolution Network
IDC: Invasive Ductal Carcinoma

is often challenging to generalize through AI modelling, thereby making it hard to deliver standard of care.

The interpretability of AI models also represents an essential challenge that matters to trust levels perceived by pathological and clinical professionals. In the absence of exploration of ethical and timely explanations of model behavior and outputs clinicians may be unwilling to trust AI generated suggestions. Additionally, lack of regulatory certainty regarding the utilization of AI tools in the clinical environment causes additional hesitation to transfer to practice. These limitations are minimal by adopting data-centric approach, as well as external auditing and ethical oversight will play vital roles in creating fair and successful AI models and methods in pathology practice.

Clinical integration and workforce readiness

To make AI tools clinically applicable, it is necessary that they are well-validated and materialize into being aligned with the current clinical workflow. Although pilot studies report enhanced quality of diagnosis with the help of AI, there are doubts about it among healthcare professionals. The solution to this barrier does not exist in the technical aspect of integration alone but a workforce development strategy of upskilling and confidence training over AI-enabled systems.

The readiness of the future includes incorporating the training on AI in education in pathology, developing the collaboration with other areas of medicine, as well as data scientists and engineers and the development of the guideline on the application of AI in diagnostics and easy access to it. Participation in such programs is of special importance to low-resource countries, like the Philippines, where the availability of specialists trained at the level, as well as infrastructure in form of laboratories is scarce.

Benchmarking AI tools through comparative metrics

The recent rise of artificial intelligence (AI) in the digital pathology domain has undoubtedly altered the landscape of histopathological diagnostics. As in low-resource settings such as the Philippines, the ability to compare the characteristics of AI model performance is important, including feature counts, model architecture, sensitivity, specificity and area under the curve (AUC). Ultimately, a tabular representation of these performance metrics can help facilitate informed decision-making.

As an example, McGenity et al.,[52] mentioned in their paper that employing AI models based on large whole-slide image datasets enabled them to achieve 96.3% sensitivity and 93.3% specificity as the diagnostic accuracies. This showed that AI systems are not only capable of mimicking but also at times even outdoing the performance of the human pathologists. In a similar vein, the works of Talo and Alom et al.,[53,54] have proven steady performance of the convolutional neural networks and transfer learning methods across various histopathological tasks, allowing the reinforcement of the strength of these architectures even though different diseases are involved. The recent launch of a foundation model like Virchow, trained on more than a million digital pathology slides, has not only confirmed the generalization power of AI across different tissue types and diagnostic settings but has also increased it as reported by Vorontsov et al.[55] To these developments, Allen[56] mentioned the formation of new frameworks for the systematic comparison of AI-based digital pathology tools which ensure the availability of practical metrics for the evaluation of the model performance under real-world conditions. The healthcare stakeholders will be able to tell which AI model best fits their current evidence-based practice and local clinical priorities by having these findings presented in comparative tables (Table 2).[52-56]

Scalability and evidence-based implementation in the Philippine context

Such advanced models like Virchow, trained on more than 1.5 M digital slides, have demonstrated an AUC above 0.95 in detecting common and rare cancers, rendering them highly valuable in settings where diagnostic capacity is limited. Besides these, validation protocols using cross-validation and external datasets as pointed out in many recent reviews serve to buttress these AI tools' strength and generalizability.

For the case in the Philippines, given the problems with delayed diagnostics and limited specialists, validation becomes even more important. In addition to providing clarity with respect to AI model performance, comparative tables allow decision-makers and technology adopters to prioritize tools that are proven to work in realistic environments. This structured process promotes transparency, enhances clinician trust and fosters the modernization of pathology services through data-driven scalable AI integration.

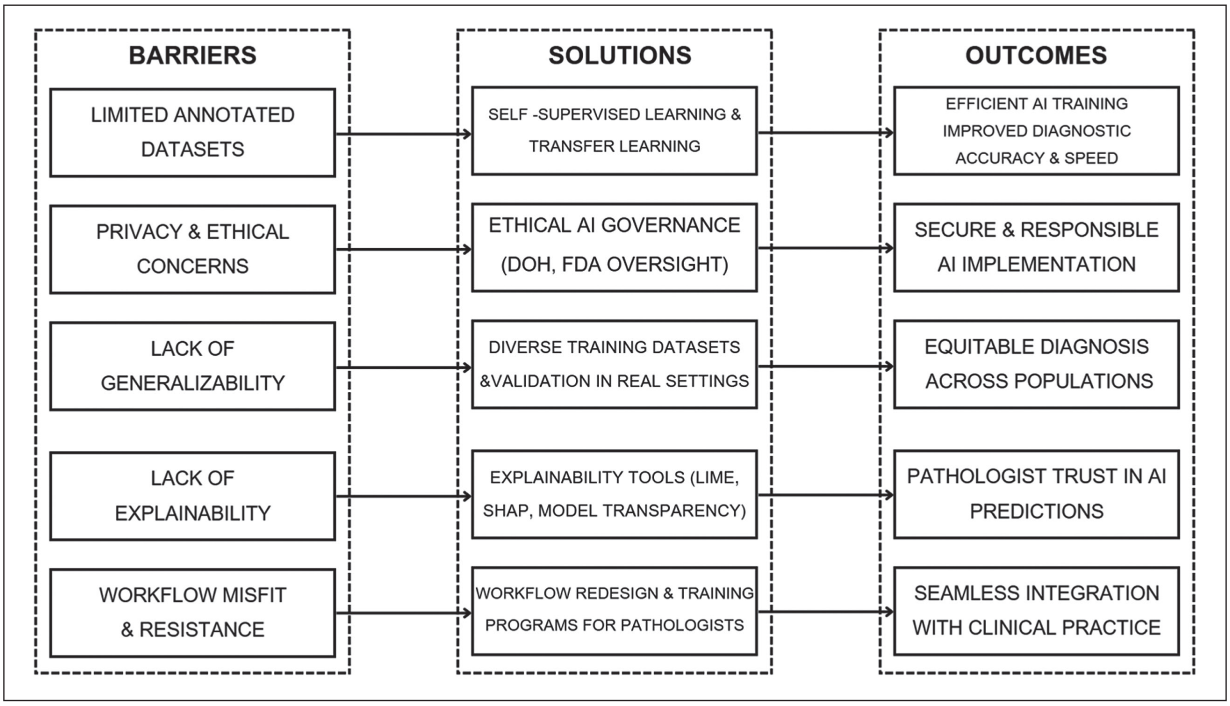

Figure 2. Key barriers in the implementation of AI in pathology.

AI implementation in pathology flow diagram

The flow diagram (Figure 2) illustrates the key barriers to implementing artificial intelligence (AI) in pathology and maps them to corresponding enablers or solutions that address these challenges, ultimately leading to improved clinical outcomes. For instance, the lack of annotated datasets can be mitigated by using self-supervised and transfer learning techniques, enabling efficient AI model training. Privacy and ethical concerns are countered through robust AI governance frameworks and oversight by institutions like the DOH and FDA. Generalizability issues are resolved by using diverse datasets and validating AI tools in real-world settings to ensure equitable diagnostics across different populations. The barrier of AI explainability is addressed through tools like LIME and SHAP, which increase transparency and build trust among pathologists. Lastly, resistance to AI integration due to workflow misalignment is overcome by redesigning clinical workflows and providing training programs, promoting smooth adoption and use of AI in daily pathology practice.

CONCLUSION

Artificial Intelligence (AI) is revolutionizing the field of pathology, particularly in resource-constrained settings like the Philippines. By leveraging machine learning (ML) and deep learning (DL) techniques, AI enhances diagnostic accuracy, speeds up workflows and supports clinical decision-making. Tools such as convolutional neural networks (CNNs) and transfer learning models like ResNet and VGG have demonstrated remarkable success in tumor detection, biomarker evaluation and predictive analytics. These advancements not only improve diagnostic precision but also enable personalized medicine, addressing the challenges of delayed diagnostics and limited access to specialized care in underserved regions. However, AI is not a replacement for pathologists; instead, it complements their expertise, fostering a collaborative intelligence model that combines human judgment with AI's ability to identify complex patterns.

Despite its transformative potential, the integration of AI into pathology faces significant barriers, including the lack of annotated datasets, privacy concerns and limited generalizability of models. Ethical and regulatory frameworks, along with tools like LIME and SHAP, are essential to build trust and transparency among clinicians. Additionally, workforce readiness through structured training programs is critical to ensure smooth adoption of AI technologies. For the Philippines, addressing these challenges requires investments in infrastructure, national support for digital innovation and collaboration between hospitals, universities and technology providers. While AI alone cannot solve systemic healthcare issues, its prudent implementation can fill critical gaps in diagnostics and remote access, improving patient outcomes and advancing the country's healthcare system.

STATEMENT OF AUTHORSHIP

All authors certified fulfillment of ICMJE authorship criteria.

DATA AVAILABILITY STATEMENT

Datasets generated and analyzed are included in the published article.

AUTHOR DISCLOSURE

The authors declared no conflict of interest. Grammarly was used for grammar checking and minor guidance on research direction; all content and conclusions are the author’s own.

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