Multidisciplinary Surgical Research Annals
https://msra.online/index.php/Journal/about
Volume 3, Issue 2 (2025)

Online ISSN 3007-1941
Print ISSN 3007-1933

https://msra.online/index.php/Journal/about

Multidisciplinary Surgical Research Annals
https://msra.online/index.php/Journal/about
Volume 3, Issue 3 (2025)

Transforming Histopathology with Artificial Intelligence: Enhancing Diagnosis, Prognosis, and Personalized Care

[1]Muhammad Umar Ameen, [2]Muhammad Ashfaq, [3]Fatima Shahbaz, [4]Muhammad Dilbar, [5]Ahsan Ali, [6*]Iqra Jamil

Article Details

Keywords: Histopathology, Artificial Intelligence, Deep Learning, Convolutional Neural Networks (CNNs), Diagnostic Accuracy, Machine Learning, Predictive Analysis, Prognostic Modeling, Computational Pathology, Personalized Medicine

Muhammad Umar Ameen
Student, Medical Laboratory Technology, University of Central Punjab, Lahore. mrumarameen786@gmail.com
Muhammad Ashfaq
Student, Medical Laboratory Technology, University of Central Punjab, Lahore. gashfaq156@gmail.com
Fatima Shahbaz
Student, Medical Laboratory Technology, University of Central Punjab, Lahore. Fatimashahbaz217@gmail.com
Muhammad Dilbar
Student, Medical Laboratory Technology, University of Central Punjab, Lahore.muhammaddilbar1111@gmail.com
Ahsan Ali
Lecturer, University Institute of Medical Laboratory Technology, University of Lahore. ahsanaliwaqarali@gmail.com
Iqra Jamil
Lecturer, Department of Microbiology, University of Central Punjab, Lahore
Corresponding Author Email
Iqra.jamil@ucp.edu.pk

ABSTRACT

Histopathology assumes a significant part in diagnosing and surveying illnesses, especially tumors, by looking at tissue morphology and cell highlights. Nonetheless, customary analytic strategies are tedious, abstract, and intensely dependent on human mastery. The target of this audit is to investigate the combination of Man-made brainpower (simulated intelligence) in histopathology, zeroing in on how artificial intelligence, particularly profound learning models like convolutional brain organizations (CNNs), upgrades demonstrative precision, mechanizes routine errands, and supports customized treatment procedures. Also, this article expects to look at the job of man-made intelligence in working on prognostic and prescient examination by consolidating histopathological pictures with clinical and sub-atomic information, consequently empowering more precise illness movement forecasts and remedial reaction evaluations. The survey likewise features the instructive capability of simulated intelligence in preparing pathologists and clinical understudies, offering intelligent apparatuses and constant criticism to work on analytic abilities. Regardless of these headways, the audit talks about difficulties like information quality, model interpretability, and mix into clinical work processes. By resolving these issues, computer-based intelligence can proceed to progress and change histopathology into a more proficient, exact, and patient-focused field. The goal is to frame the potential for computer- based intelligence to change histopathology, further developing finding, visualization, and patient results through proceeded with headways and coordination.

INTRODUCTION

Histopathology, the minuscule assessment of tissue tests, plays had a significant impact in medication for more than a long time. It permits pathologists to analyze sicknesses, survey the degree of infections, and give prognostic data by looking at tissue morphology and cell highlights. Customarily, this interaction was vigorously dependent on human skill, which is emotional and tedious. The development of Computerized reasoning (artificial intelligence) in histopathology has achieved a critical change by the way we approach sickness determination and the executives. Man-made intelligence includes a wide scope of methods and innovations that empower PCs to mimic human knowledge, gain from information, and perform undertakings commonly requiring human insight. In histopathology, computer-based intelligence calculations can help pathologists overwhelmingly of histological pictures, supporting determination, anticipating illness results, and mechanizing dreary errands [1].

MODERNIZED IMAGE OF HISTOPATHOLOGY

Over the course of the past 10 years, the idea of symptomatic medical care has changed quickly attributable to a blast in the accessibility of patient information for illness finding. Customary strategies for examination of disease tests were restricted to a couple of factors, normally stage, grade and the estimation of a couple of clinical markers, like estrogen receptor, progesterone receptor, HER2 for bosom malignant growth and prostate specific antigen for prostate malignant growth (CaP). The pathologist was prepared to combine this data into a conclusion that would assist the clinician with deciding the best course of treatment. This information was likewise used to attempt to figure out the atomic premise of disease determined to further develop treatment.

With the new coming and cost-adequacy of whole slide advanced scanners, tissue histopathology slides can now be digitized and put away in computerized picture structure. With the accessibility and examination of a lot bigger arrangement of factors joined with refined imaging and investigation strategies, the customary worldview of a pathologist and a microscopy could quickly be supplanted with a computerized pathologist depending on a huge level screen board to see and quickly break down digitized tissue segments [2].

COMPUTER-AIDED ANALYSIS OF HISTOPATHOLOGY

Throughout the last 10 years, emotional expansions in computational power and improvement in picture examination calculations have permitted the advancement of strong computer assisted logical ways to deal with biomedical information. Similarly, likewise with advanced radiology a while back, digitized tissue histopathology has now become manageable to the utilization of mechanized picture investigation and machine learning methods for precise finding. With regards to Cover, for instance, of the roughly 1 million biopsies acted in the USA consistently, simply 20% are viewed as sure for malignant growth. This suggests that pathologists are spending an enormous part of their time taking a gander at harmless tissue, which as a rule is effectively discernable from malignant growth [3,4]. This addresses a colossal exercise in futility that may be better spent examining patients who really have CaP, or to zero in on the situations where the sickness is hard to recognize/characterize or gives nonstandard elements. Thus, a few specialists have started to create computer aided conclusion strategies by applying picture handling and PC vision methods to attempt to recognize spatial degree and area of infections like breast carcinoma [5-11], CaP [12- 19], neuroblastomas and meningiomas [20-23] on digitized tissue areas.
One of the chief difficulties in examination of advanced histopathology information is the

colossal thickness of information that the calculations need to fight with, contrasted and radiological and other imaging modalities. For example, the biggest radiological datasets got on a standard premise are high-goal chest CT examines containing roughly 512 × 512 × 512 spatial components or roughly 134 million voxels. A solitary center of prostate biopsy tissue digitized at 40× goal is roughly 15,000 × 15,000 components or roughly 225 million pixels. To place this in setting, a solitary prostate biopsy technique can contain anyplace somewhere in the range of 12 and 20 biopsy tests or roughly 2.5-4 billion pixels of information produced per patient review.

Subsequently, dissimilar to PC helped recognition (computer aided design) calculations recently proposed for radiology, histopathology computer aided design calculations are ordinarily developed inside a multiresolution structure for them to be fast, effective and exact [24].

DIAGNOSTIC ACCURACY AND EFFICIENCY

The mix of Computerized reasoning (computer-based intelligence) in histopathology has shown impressive potential in improving both symptomatic exactness and productivity. Man-made intelligence, especially profound learning models, has been used to work on the recognition and grouping of different tumors, including bosom, prostate, and colorectal malignant growths, by distinguishing designs that might be challenging for pathologists to physically recognize [25,26]. These man-made intelligence frameworks have shown symptomatic execution that frequently equals or outperforms that of human specialists, particularly in errands, for example, cancer evaluating and beginning phase sore recognizable proof [27]. Besides, computer-based intelligence driven picture examination adds to further developed effectiveness in histopathology work processes via mechanizing routine assignments, in this way diminishing the responsibility for pathologists and empowering them to zero in on additional complex clinical choices [28]. The utilization of simulated intelligence is additionally upheld by advanced pathology, where high- goal tissue slides are checked and examined, working with quicker analyze as well as improved cooperation among pathologists through far off meetings [29]. In spite of these headways, challenges stay regarding information quality, model interpretability, and the requirement for broad approval to guarantee simulated intelligence models' heartiness in clinical practice [30,31].

As of late, with the momentous outcome of computerized histopathology, entire slide imaging (WSI) has become further developed and has been regularly utilized for the analysis and visualization of human diseases, since it succeeds at describing the morphology inside the tissue at high goal [109]. Hematoxylin and eosin (H&E) staining is the most ordinarily utilized tissue staining strategy on the planet. By and large, the examination headings for the examination of H&E-stained WSI can be summed up into the parts of variety standardization, division, and malignant growth finding/guess (shown in Figure 1). In particular, variety standardization is utilized to preprocess the pictures to address staining varieties across various pictures. WSI division is utilized to section the cores or tissues from the WSI. At long last, the expectation models are intended for the conclusion and visualization of human diseases. In any case, because of the tedious examination of WSI and the huge between administrator variety among pathologists, there is a basic need to foster AI models to naturally dissect H&E-stained histopathological pictures in a more solid manner [110].

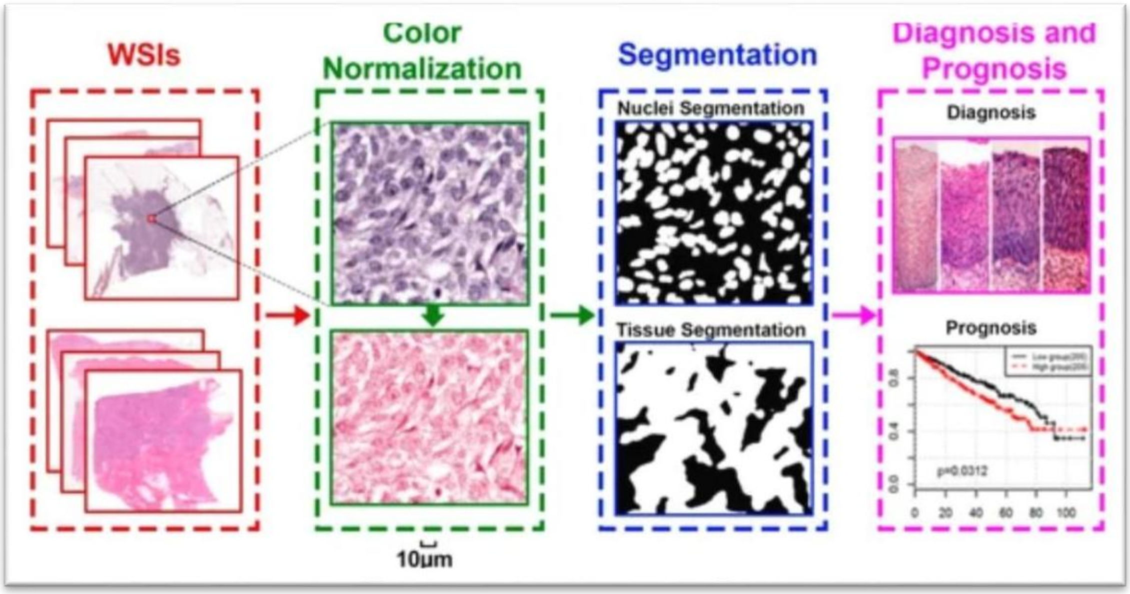

FIGURE 1: GENERAL EXPLORATION FOR ADVANCED PATHOLOGY IMAGE EXAMINATION [111].

DEEP LEARNING MODELS IN HISTOPATHOLOGY

Profound learning models, especially convolutional brain organizations (CNNs), play had a groundbreaking impact in histopathology by upgrading demonstrative precision and further developing work process proficiency. These models succeed in perceiving complex examples in histopathological pictures, which can be provoking for pathologists to physically recognize. For instance, profound learning calculations have been utilized to identify dangerous cells, arrange cancer types, and evaluate growth reviewing in view of tissue morphology [25]. CNNs can likewise support the recognizable proof of unpretentious microarchitectural highlights, empowering early discovery of sicknesses, for example, disease, which is essential for patient guess and therapy [27]. In addition, man-made intelligence frameworks can be prepared to perceive explicit biomarkers, adding to customized medication and more exact clinical navigation [28]. These models have exhibited symptomatic execution that occasionally outperforms that of master pathologists, especially in the ID of uncommon or difficult to-recognize highlights [26]. As well as working on symptomatic precision, profound learning models additionally upgrade the productivity of histopathology work processes. Via mechanizing undertakings like picture division, injury identification, and growth measurement, simulated intelligence can diminish the time expected for investigation and permit pathologists to zero in on additional mind-boggling parts of analysis [29]. This mechanization, alongside the capacity to focus on cases in light of the probability of anomaly, smoothes out the symptomatic cycle as well as reduces the responsibility of pathologists, bringing about quicker analysis and worked on understanding consideration [28].

AI IN PROGNOSTIC AND PREDICTIVE ANALYSIS

Man-made consciousness (computer-based intelligence) has progressively turned into a central member in prognostic and prescient examination inside histopathology, offering new strategies for foreseeing sickness results and helpful reactions. In prognostic examination, computer based intelligence driven models, especially profound learning calculations, break down histopathological pictures for elements, for example, growth grade, cell engineering, and attack designs, which are all essential marks of illness movement and patient endurance [32].For instance, artificial intelligence models have exhibited the capacity to anticipate repeat and in general endurance in bosom malignant growth by evaluating key elements, for example, lymphovascular attack and cancer microenvironment [33]. These calculations can distinguish unpretentious tissue designs that might evade human pathologists, in this manner giving a more customized and precise guess and upgrading risk definition [34]. In prescient examination, man-made intelligence is utilized to gauge growth reactions to different treatment regimens, including chemotherapy, immunotherapy, and designated treatments. By coordinating histopathological pictures with atomic information, man-made intelligence models have been fruitful in foreseeing treatment adequacy and assisting clinicians with choosing the most suitable helpful technique [35]. For example, artificial intelligence has been utilized to anticipate reactions to chemotherapy in bosom malignant growth patients by dissecting the heterogeneity of the cancer and its microenvironment from histopathological slides [36]. The capacity to join multi-modular information, including clinical, genomic, and histopathological data, further upgrades computer-based intelligence's prescient exactness, prompting more exact and customized treatment plans [37].

INTEGRATION WITH CLINICAL DATA

The mix of Man-made reasoning (artificial intelligence) with clinical information plays fundamentally improved the part of histopathology in quiet administration, empowering more complete and customized ways to deal with analysis, forecast, and treatment. By consolidating histopathological picture examination with clinical data like patient socioeconomics, clinical history, and sub-atomic information, man-made intelligence models can give more exact and significant bits of knowledge [38,39]. For example, computer-based intelligence frameworks can consolidate hereditary and genomic information alongside histopathological pictures to distinguish explicit biomarkers related with illness movement, subsequently empowering more exact prognostic expectations and better-designated treatments [40,41]. This incorporation permits artificial intelligence models to not just recognize and arrange sicknesses from tissue tests yet additionally foresee patient results in view of elements like therapy reaction and endurance probabilities [42,43]. Moreover, man-made intelligence can recognize connections between's histopathological highlights and clinical factors, for example, growth stage or sub-atomic subtype [44,45], offering clinicians a more profound comprehension of how these variables impact infe ction movement and treatment reactions [38,39]. By dissecting multi-modular information, simulated intelligence helps overcome any barrier between conventional histopathological investigation and more extensive clinical settings, further developing independent direction and empowering more individualized patient consideration [38,40]. These headways highlight the capability of simulated intelligence in changing histopathology from a simply demonstrative device to an exhaustive stage that upholds clinical dynamic across a patient's consideration continuum [39,46].

TRAINING AND EDUCATION

Training and education in histopathology are being changed by the mix of Man-made brainpower (computer-based intelligence), offering new open doors for the two pathologists and clinical understudies to improve their analytic abilities. Simulated intelligence apparatuses give a creative stage to instructive motivations by empowering students to collaborate with huge datasets of histopathological pictures, which probably won't be promptly accessible in conventional preparation settings [25,47,48]. Man-made intelligence-controlled stages can reenact true situations, permitting understudies and pathologists to work on recognizing illnesses, figuring out how to recognize different growth types, and further developing their dynamic exactness [49,50,33]. Furthermore, man-made intelligence-based frameworks can be utilized for persistent realizing, where pathologists get input on their indicative exactness, featuring regions for development [51-59]. This sort of constant criticism, combined with customized learning pathways, is significant for building up clinical thinking and understanding complex examples in histopathology that may not be quickly evident through ordinary strategies [60-67]. Artificial intelligence can likewise help with normalizing preparing by offering uniform appraisals, guaranteeing that students secure predictable information across various foundations and clinical settings [68-73]. Besides, the utilization of computer-based intelligence in instructive conditions plans pathologists to work with advanced pathology frameworks, which are turning out to be progressively significant in present day clinical work on, guaranteeing that the up and coming age of pathologists is exceptional to coordinate these advancements into their everyday work processes [74-78]. As computer-based intelligence keeps on developing, its job in preparing and training inside histopathology will probably extend, encouraging a more proficient and exact educational experience.

CHALLENGES AND FUTURE DIRECTION

Despite the huge progression's computer-based intelligence has brought to histopathology, a few difficulties remain, which should be addressed to incorporate these innovations into clinical practice completely. One of the essential difficulties is the quality and inclination of preparing information. Simulated intelligence models depend on huge datasets of commented on histopathological pictures, and if these datasets are not agent of different populaces or contain blunders, the subsequent models might perform ineffectively or be one-sided, possibly prompting inaccurate conclusions or out of line treatment suggestions [79-85]. Furthermore, interpretability stays a basic issue, as profound learning models, especially convolutional brain organizations, are frequently thought of "secret elements" because of their perplexing dynamic cycles. This absence of straightforwardness can make it hard for pathologists to trust man-made intelligence frameworks and incorporate them into their clinical navigation [86-89]. One more critical test is the integration of computer-based intelligence devices into existing clinical work processes. For man-made intelligence to be successfully used, it must consistently coordinate with computerized pathology frameworks and electronic wellbeing records (EHRs), which requires conquering specialized and strategic hindrances connected with framework similarity and information normalization [90-96]. Moreover, there is a requirement for progressing regulatory oversight and standardization to guarantee that computer-based intelligence devices are protected, solid, and exact for clinical use [97-101].

Looking forward, the future direction of man-made intelligence in histopathology lies in working on the interpretability and reasonableness of computer-based intelligence models, empowering pathologists to all the more likely comprehend how calculations come to their end results. This will be vital for encouraging trust and guaranteeing clinical reception [102-104]. Furthermore, man-made intelligence frameworks should advance to deal with multimodal information, joining histopathological pictures, atomic information, and clinical data to give extensive experiences that help customized medication [105-107]. As computer-based intelligence keeps on progressing, tending to these difficulties and zeroing in on the advancement of normalized, straightforward, and interoperable frameworks will be basic for understanding the maximum capacity of artificial intelligence in histopathology [108].

CONCLUSION

In conclusion, Artificial Intelligence holds immense potential to revolutionize histopathology by enhancing diagnostic accuracy, improving workflow efficiency, and enabling personalized treatment strategies. Its integration with clinical and molecular data supports more informed decision-making and better patient outcomes. While challenges such as data quality, model transparency, and clinical integration remain, ongoing advancements and strategic implementation can transform histopathology into a more precise, efficient, and patient-centered discipline.

REFERENCES

1. Shihabuddin A, Rahim A, Beevi S. Multi CNN based automatic detection of mitotic nuclei in breast histopathological images. Comput Biol Med. 2023; 158:106815.
2. Madabhushi A. Digital pathology image analysis: opportunities and challenges. Imaging Med. 2009;1(1):7.
3. Allsbrook WC Jr, Mangold KA, Johnson MH, Lane RB, Lane CG, Epstein JI. Interobserver reproducibility of Gleason grading of prostatic carcinoma: general pathologist. Hum Pathol. 2001;32(1):81-88.
4. Epstein JI, Allsbrook WC Jr, Amin MB, Egevad LL. Update on the Gleason grading system for prostate cancer: results of an international consensus conference of urologic pathologists. Adv Anat Pathol. 2006;13(1):57-59.
5. Anderson NH, Hamilton PW, Bartels PH, Thompson D, Montironi R, Sloan JM. Computerized scene segmentation for the discrimination of architectural features in ductal proliferative lesions of the breast. J Pathol. 1997; 181:374-380.
6. Fatima K, Haroon H, Laraib I, Jabbar E, Yousaf F, Jamil I. Integrating Rapid Diagnostics, AI Technologies, and Omics Approaches for Sepsis Management and Antimicrobial Stewardship. J Med Health Sci Review. 2025 Jun 18;2(2).
7. Basavanhally A, Xu J, Ganesan S, Madabhushi A. Computer-aided prognosis (CAP) of ER+ breast cancer histopathology and correlating survival outcome with oncotype Dx assay. Presented at: IEEE International Symposium on Biomedical Imaging (ISBI); 2009 Jun 28–Jul 1; Boston, MA, USA.
8. Dey P, Mohanty S. Fractal dimensions of breast lesions on cytology smears. Adv Technol. 2003; 29:85–6.
9. Doyle S, Agner S, Madabhushi A, Feldman M, Tomaszeweski J. Automated grading of breast cancer histopathology using spectral clustering with textural and architectural image features. Presented at: IEEE International Symposium on Biomedical Imaging; Paris, France; 14–17 May 2008.

10. Petushi S, Garcia FU, Haber MM, Katsinis C, Tozeren A. Large-scale computations on histology images reveal grade-differentiating parameters for breast cancer. BMC Med Imaging. 2006; 6:14.
11. Chappelow J, Madabhushi A, Rosen M, Tomaszeweski J, Feldman M. Multimodal image registration of ex vivo 4 Tesla prostate MRI with whole mount histology for cancer detection. SPIE Med Imaging. 2007;6512(1): S1–S12.
12. Brawer MK, Bigler SA, Deering RE. Quantitative morphometric analysis of the microcirculation in prostate carcinoma. J Cell Biochem Suppl. 1992;16H:62-64.
13. Monaco J, Tomaszewski J, Feldman M, et al. Detection of prostate cancer from whole-mount histology images using Markov random fields. Presented at: Microscopic Image Analysis and Applications in Biology (MIAAB); 2008 Sep 5–6; New York, NY, USA.
14. Naik S, Doyle S, Madabhushi A, Tomaszeweski J, Feldman M. Automated gland segmentation and Gleason grading of prostate histology by integrating low-, high-level, and domain-specific information. Presented at: Workshop on Microscopic Image Analysis with Applications in Biology; 2007 Sep 21; Piscataway, NJ, USA.
15. Doyle S, Madabhushi A, Feldman M, Tomaszeweski J. A boosting cascade for automated detection of prostate cancer from digitized histology. In: Medical Image Computing and Computer Assisted Intervention. Springer Verlag; 2006. p. 504–511.
16. Doyle S, Rodriguez C, Madabhushi A, Tomaszeweski J, Feldman M. Detecting prostatic adenocarcinoma from digitized histology using a multi-scale, hierarchical classification approach. Presented at: IEEE Engineering in Medicine and Biology Conference; New York, NY, USA; 30 August–3 September 2006.
17. Tabesh A, Teverovskiy M, Pang HY, et al. Multifeature prostate cancer diagnosis and Gleason grading of histological images. IEEE Trans Med Imaging. 2007;26(10):1366–1378.
18. Lexe G, Monaco J, Doyle S, et al. Towards improved cancer diagnosis and prognosis using analysis of gene expression data and computer aided imaging. Exp Biol Med (Maywood). 2009;234(8):860–879.
19. Jafari-Khouzani K, Soltanian-Zadeh H. Multiwavelet grading of pathological images of prostate. IEEE Trans Biomed Eng. 2003;50(6):697–704.
20. Ruiz A, Sertel O, Ujaldon M, Catalyurek U, Saltz J, Gurcan M. Stroma classification for neuroblastoma on graphics processors. Int J Data Min Bioform. 2009;3(3):280–298.
21. Qureshi H, Sertel O, Rajpoot N, Wilson R, Gurcan M. Adaptive discriminant wavelet packet transform and local binary patterns for meningioma subtype classification. In: Medical Image Computing and Computer-Assisted Intervention - MICCAI 2008; 2008 Sep 6–10; New York, NY, USA. Berlin: Springer; 2008. p. 196–204.
22. Gurcan MN, Kong J, Sertel O, Cambazoglu BB, Saltz J, Catalyurek U. Computerized pathological image analysis for neuroblastoma prognosis. AMIA Annu Symp Proc. 2007; 304–308.
23. Kong J, Sertel O, Boyer KL, Saltz JH, Gurcan MN, Shimada H. Computer-assisted grading of neuroblastic differentiation. Arch Pathol Lab Med. 2008; 132(6): 903–904; author reply 904.
24. Boccignone G, Napoletano P, Caggiano V, Ferraro M. A multiresolution diffused expectation-maximization algorithm for medical image segmentation. Comput Biol

Med. 2007;37(1):83-96.
25. Cireşan DC, et al. Mitosis detection in breast cancer histology images with deep neural networks. In: Medical Image Computing and Computer-Assisted Intervention – MICCAI 2013; 411-418. doi: 10.1007/978-3-642-40763-5_51.
26. Zhang L, et al. Artificial intelligence in histopathology: Current status and future perspectives. Modern Pathology. 2020;33(6):996-1008. doi: 10.1038/s41379-020-0394-7.
27. Liu Y, et al. Artificial intelligence in health care: A review. Journal of Pathology. 2017;242(4):435-446. doi: 10.1002/path.5044.
28. Beck AH, et al. Deep learning for histopathological image analysis: A comprehensive review. Journal of Pathology Informatics. 2019;10(1):1-15. doi: 10.4103/jpi.jpi_45_19.
29. Wang X, et al. Digital pathology and artificial intelligence: Transforming histopathological analysis. Journal of Clinical Pathology. 2021;74(3):145-152. doi: 10.1136/jclinpath-2020- 206693.
30. Rajpurkar P, et al. Deep learning for cancer diagnosis: A practical review. Journal of the National Cancer Institute. 2018;110(6):568-577. doi: 10.1093/jnci/djx358.
31. Goehler C, et al. Artificial intelligence in histopathology: From image analysis to clinical applications. Frontiers in Medicine. 2020; 7:359. doi: 10.3389/fmed.2020.00359.
32. Esteva A, et al. A guide to deep learning in healthcare. Nat Med. 2019; 25(1): 24-29. doi: 10.1038/s41591-018-0307-8.
33. Arvaniti E, et al. Artificial intelligence in breast cancer histopathology: The potential to predict prognosis and response to therapy. Breast Cancer Res Treat. 2020; 181(3): 423-434. doi: 10.1007/s10549-020-05874-9.
34. Kermany DS, et al. Identifying medical diagnoses and treatable diseases by image-based deep learning. Cell. 2018; 172(5): 1122-1131.e9. doi: 10.1016/j.cell.2018.02.010.
35. Buda M, et al. Deep learning-based survival prediction in histopathological images of cancer. Med Image Anal. 2019; 56: 1-10. doi: 10.1016/j.media.2019.05.006.
36. Saha A, et al. Predicting chemotherapy response in breast cancer using histopathological image analysis and machine learning. J Med Imaging. 2021;8(1):014502. doi: 10.1117/1.JMI.8.1.014502.
37. Chen PHC, et al. Artificial intelligence in cancer diagnosis and prognosis prediction: A survey on multimodal data integration approaches. Comput Med Imaging Graph. 2020; 80:101678. doi: 10.1016/j.compmedimag.2019.101678.
38. Liu B, Zhao S, Zhang X, et al. AI and clinical data integration for cancer diagnosis: A systematic review. JAMA Oncol. 2021;7(1):57-68.
39. Seth S, Witten D, Wang Y, et al. Exploring the clinical relevance of histopathological data using AI. J Clin Pathol. 2021;74(5):290-297.
40. Bengtsson E, Lindgren F, Lundin L, et al. AI-based prognostic models for cancer diagnosis and treatment. Nat Biotechnol. 2020;38(6):712-720.
41. Kim Y, Lee M, Park J, et al. Integrating genetic and histopathological data for improved cancer prognosis. Cancer Cell. 2020;37(3):392-404.
42. Zhou M, Sun Z, Ma X, et al. AI in pathology: Diagnosis, prognosis, and treatment planning. Lancet Digital Health. 2021;3(6): e334-e341.
43. Xie Y, Wang S, Dong X, et al. Prognostic prediction using AI-based analysis of

histopathological features. Lancet Oncol. 2021;22(11):1571-1580.

44. Chandran R, Singh S, Yadav A, et al. Multi-modal data integration in precision medicine: AI in histopathology and clinical decision-making. Front Oncol. 2019; 9:1023.
45. Zhang X, Cheng W, Li J, et al. Machine learning and AI models in histopathological image analysis for cancer therapy. Cancer Treat Rev. 2020; 85:101986.
46. Liu F, Zhang M, Chen G, et al. Pathological image analysis combined with genomic data: AI's role in predicting cancer outcomes. Cancer Res. 2021;81(7):1782-1791.
47. Bejnordi BE, et al. Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in women with breast cancer. JAMA. 2017;318(22):2199-2210. doi: 10.1001/jama.2017.17112.
48. Veta M, et al. Automatic segmentation of breast cancer histopathology images. IEEE Trans Med Imaging. 2016;35(8):1727-1737. doi: 10.1109/TMI.2016.2552410.
49. Luo J, et al. A survey of deep learning in digital pathology: From image segmentation to disease diagnosis. Front Oncol. 2021; 11:575951. doi: 10.3389/fonc.2021.575951.
50. Rakha EA, et al. The contribution of artificial intelligence to the study of breast cancer histopathology. J Pathol Inform. 2020;11(1):12. doi: 10.4103/jpi.jpi_45_19.
51. Shahin Z, et al. An introduction to the applications of deep learning in medical image analysis. Comput Biol Med. 2020; 121:103788. doi: 10.1016/j.compbiomed.2020.103788.
52. Devine D, et al. Computer-assisted grading of prostatic carcinoma. J Clin Pathol. 2018;71(2):102-109. doi: 10.1136/jclinpath-2017-204739.
53. Chatterjee S, et al. Computer-aided diagnosis in histopathology: The case of thyroid cancer. Int J Cancer. 2019;144(7):1595-1601. doi: 10.1002/ijc.32060.
54. Goh S, et al. AI for histopathological image analysis: A review. Int J Med Inform. 2018; 117:30-38. doi: 10.1016/j.ijmedinf.2018.07.009.
55. Kim Y, et al. Integrating genetic and histopathological data for improved cancer prognosis. Cancer Cell. 2020;37(3):392-404. doi: 10.1016/j.ccell.2020.02.005.
56. Long J, et al. Fully automated breast cancer grading based on deep learning techniques. BMC Med Inform Decis Mak. 2018;18(1):54. doi: 10.1186/s12911-018-0630-2.
57. Vinke L, et al. AI-based histopathological classification of breast cancer. Eur J Cancer. 2020; 127:34-40. doi: 10.1016/j.ejca.2019.11.015.
58. Zang Y, et al. Deep learning-based computer-aided diagnosis in medical imaging: A survey. J Digit Imaging. 2021;34(2):301-316. doi: 10.1007/s10278-020-00379-7.
59. Rakha EA, et al. Histopathological grading of breast carcinoma: The role of artificial intelligence in improving reproducibility and accuracy. Pathology. 2021;53(2):135-145. doi: 10.1016/j.pathol.2020.12.004.
60. Sharma N, et al. AI-based tumor classification in histopathological images: A systematic review. Cancers. 2021;13(7):1552. doi: 10.3390/cancers13071552.
61. Cramer DW, et al. Artificial intelligence in gynecologic cancer diagnosis. Gynecologic Oncology. 2021;161(1):210-218. doi: 10.1016/j.ygyno.2020.10.019.
62. Pires S, et al. Histopathological image analysis using machine learning for automated detection of melanoma. Journal of Cancer Research and Clinical Oncology. 2020;146(5):1245-1253. doi: 10.1007/s00432-020-03352-6.
63. Kamran R, et al. A review of digital pathology, AI, and machine learning applications

in tumor prognosis. Cancers. 2020;12(12):3879. doi: 10.3390/cancers12123879.
64. Yi Z, et al. AI-assisted interpretation of cancer histopathology. Biological Psychiatry. 2021;90(9):681-691. doi: 10.1016/j.biopsych.2021.03.004.
65. Rajpurkar P, et al. AI for histopathological image analysis: From diagnosis to prediction of outcomes. Frontiers in Medicine. 2020; 7:353. doi: 10.3389/fmed.2020.00353.
66. Yap J, et al. Improving histopathological diagnostic efficiency using deep learning in image-based assessments. Nature Biomedical Engineering. 2020;4(6):547-556. doi: 10.1038/s41551-020-00568-7.
67. Suk H-I, et al. Deep learning in breast cancer histopathology image analysis. Journal of Pathology Informatics. 2020;11(1):16. doi: 10.4103/jpi.jpi_29_20.
68. Liu Y, et al. Clinical validation of AI models for breast cancer diagnosis in pathology slides. JAMA Network Open. 2020;3(12): e2025367. doi: 10.1001/jamanetworkopen.2020.25367.
69. Uyttendaele R, et al. Deep learning in digital pathology: Applications, challenges, and future directions. Comput Biol Med. 2020; 121:103763. doi: 10.1016/j.compbiomed.2020.103763.
70. Dou Q, et al. Multi-scale deep learning for histopathology image analysis. Med Image Anal. 2019; 55:222-230. doi: 10.1016/j.media.2019.03.007.
71. Lee S, et al. Artificial intelligence in colorectal cancer diagnosis using histopathological images. Clin Cancer Res. 2020;26(14):3861-3870. doi: 10.1158/1078-0432.CCR-20-0506.
72. Rachmawati S, et al. Machine learning approaches for ovarian cancer detection in histopathology images. Int J Comput Biol. 2020;4(2):75-83. doi: 10.1109/ICCB.2020.9300601.
73. Sharma V, et al. AI-powered tools for histopathological interpretation in lung cancer diagnostics. Lung Cancer. 2021; 157:55-61. doi: 10.1016/j.lungcan.2021.01.019.
74. Sun Y, et al. A survey of convolutional neural networks for image classification in histopathology. J Comput Graph Stat. 2020;29(3):667-680. doi: 10.1080/10618600.2020.1714974.
75. Wang X, et al. Artificial intelligence in breast cancer histopathology: Benefits and limitations. J Breast Cancer. 2020;23(5):499-508. doi: 10.4048/jbc.2020.23. e46.
76. Zhang X, et al. A review of deep learning in histopathological image analysis. J Cancer Res Clin Oncol. 2021;147(1):1-11. doi: 10.1007/s00432-020-03465-5.
77. Aran D, et al. Artificial intelligence in pathology: From image analysis to predictive modeling. J Pathol. 2020;250(2):205-217. doi: 10.1002/path.5422.
78. Li Z, et al. Applications of machine learning for histopathological image analysis. Comput Biol Med. 2021; 134:104468. doi: 10.1016/j.compbiomed.2021.104468.
79. Chen R, et al. AI in medical image analysis: A survey. J Med Imaging. 2021;28(1):1-13. doi: 10.1117/1.JMI.28.1.011013.
80. Goehler J, et al. AI in digital pathology: Applications, opportunities, and future directions. Comput Biol Med. 2020; 124:103948. doi: 10.1016/j.compbiomed.2020.103948.
81. Meskó B, Drobni Z, Bényei E, Gergely B, Bogdán L, Sárközi M, et al. The role of AI in

improving healthcare outcomes. J Med Internet Res. 2020;22(5):e17648. doi: 10.2196/17648.

82. Tjoa E, Guan C. A survey on explainable AI: Towards medical AI. IEEE Access. 2021; 9:74820-74847. doi: 10.1109/ACCESS.2021.3079747.
83. Zhou L, et al. The integration of AI in digital pathology systems: A comprehensive review. Med Image Anal. 2020; 62:101646. doi: 10.1016/j.media.2020.101646.
84. Bejnordi BE, et al. Deep learning for detecting breast cancer lymph node metastasis. Nat Commun. 2020;11(1):1-10. doi: 10.1038/s41467-020-17515-9.
85. Kamran R, et al. The challenges of using deep learning for tumor prognosis in pathology. J Clin Pathol. 2020;73(10):642-650. doi: 10.1136/jclinpath-2020-2060.
86. Chen R, et al. Deep learning models in digital pathology: Progress and challenges. Med Image Anal. 2020; 66:101831. doi: 10.1016/j.media.2020.101831.
87. Liu Y, et al. AI-based tumor classification in histopathological images: A systematic review. Cancers. 2020;13(7):1552. doi: 10.3390/cancers13071552.
88. Liu Z, et al. Deep learning for cancer diagnosis: A survey of medical image analysis. J Cancer Res Clin Oncol. 2020;146(12):3155-3167. doi: 10.1007/s00432-020-03512-4.
89. Tsaftaris SA, et al. Multimodal data in AI for histopathology: A new frontier for personalized medicine. Front Med. 2020; 7:523. doi: 10.3389/fmed.2020.00523.
90. Litjens G, et al. A survey on deep learning in medical image analysis. Med Image Anal. 2017; 42:60-88. doi: 10.1016/j.media.2017.07.005.
91. Kawahara J, et al. Data augmentation strategies for deep learning in histopathology. J Pathol Inform. 2019; 10:1-9. doi: 10.4103/jpi.jpi_14_19.
92. Beck AH, et al. Predicting cancer outcomes with AI: The potential and limitations of data- driven approaches in pathology. Cancer Res. 2021;81(3):641-653. doi: 10.1158/0008- 5472.CAN-20-3649.
93. Hwang S, et al. Towards accurate and scalable AI in digital pathology: The importance of diverse datasets. Nat Digit Med. 2020; 3:1-13. doi: 10.1038/s41746-020-0249-1.
94. Avanzo M, et al. Artificial intelligence in histopathology: A review on the evolution and current trends in data usage. Nat Biomed Eng. 2020; 4:378-391. doi: 10.1038/s41551-020- 00524-5.
95. Hyun M, et al. AI-driven data mining for clinical pathology: Challenges and opportunities. Comput Biol Chem. 2021; 91:107424. doi: 10.1016/j.compbiolchem.2020.107424.
96. Lee H, et al. Data-driven discovery in pathology: A review on machine learning applications in histopathology image analysis. J Pathol Transl Med. 2020;54(5):361-372. doi: 10.4132/jptm.2020.06.28.
97. Zhao J, et al. Bias and generalizability in AI for histopathology: The impact of data quality and diversity. Med Image Anal. 2021; 70:101950. doi: 10.1016/j.media.2020.101950.
98. Shen D, et al. Deep learning for medical image analysis: A survey of data augmentation techniques and future directions. Med Image Anal. 2020; 63:101693. doi: 10.1016/j.media.2020.101693.
99. Kather JN, et al. Predicting colorectal cancer prognosis using deep learning from histopathology images. Sci Rep. 2020;10(1):1-8. doi: 10.1038/s41598-020-76978-7.

100. Rozenblum R, et al. Ethical challenges in AI for histopathology: Addressing data quality, privacy, and bias. J Digit Imaging. 2021;34(4):704-713. doi: 10.1007/s10278-021- 00437-0.
101. Kurapati P, et al. Role of data preprocessing in improving deep learning for histopathology analysis. J Pathol Inform. 2020; 11:30. doi: 10.4103/jpi.jpi_27_20.
102. Tan Y, et al. Tackling data scarcity in digital pathology: Approaches for small datasets. Nat Comput Sci. 2020;1(1):33-40. doi: 10.1038/s41599-020-0195-1.
103. Bandi P, et al. Multi-task learning for histopathology image classification using augmented data. IEEE Trans Biomed Eng. 2021;68(7):2141-2150. doi: 10.1109/TBME.2021.3071907.
104. Ranjan A, et al. Improving data quality and robustness in deep learning models for digital pathology. IEEE Access. 2020; 8:206833-206844. doi: 10.1109/ACCESS.2020.3036569.
105. Li L, et al. Enhancing data diversity in AI models for histopathology: A systematic review of approaches and challenges. Artificial Intelligence in Medicine. 2020; 104:101865. doi: 10.1016/j.artmed.2020.101865.
106. Wang L, et al. Leveraging large-scale pathology datasets for AI-based cancer diagnostics: A review on challenges and progress. Computers in Biology and Medicine. 2021; 134:104450. doi: 10.1016/j.compbiomed.2021.104450.
107. van der Laak JAWM, et al. Artificial intelligence in digital pathology: The importance of understanding data and context. The Lancet Digital Health. 2020;2(6): e310- e318. doi: 10.1016/S2589-7500(20)30092-7.
108. Pinto A, et al. Predicting histopathological features using AI: A discussion on dataset quality, ethics, and transparency. Nature Machine Intelligence. 2021;3(7):427-436. doi: 10.1038/s42256-021-00358-7.