

Digital pathology... Review of the current scenario

Anjali Goyal^{1,*}

¹Professor, Smt. N.H.L. Municipal
Medical College, India

*Author for correspondence:
Email: anjali@knee.in

Received date: July 14, 2024
Accepted date: August 20, 2024

Copyright: © 2024 Goyal A. This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Citation: Goyal A. Digital pathology... Review of the current scenario. J Clin Exp Gastroenterol. 2024;3(1):21-24.

Editorial

Histopathology, defined as study of diseased cells and tissues is the science dealing with the study of biopsies and tissues under the microscope to form a possible diagnosis based on the morphology of the cells and surrounding tissues [1].

The current histopathology practice passes through several phases that highlight specific structures in the images, starting from tissue fixation, staining with dyes like Haematoxylin and Eosin or special techniques like immunohistochemistry and immuno-fluoresce labelling followed by microscopic examination by the Pathologist. In addition to being time consuming, it also suffers from a subjective variation between the pathologists especially in reporting on quantitative parameters like the mitotic counts [2,3].

The newer age histopathology aided by a computer assisted diagnosis (CAD) is programmed to analyze the biomedical images making use of the AI based algorithms and hence proposed to reduce the manual subjectivity along with a rapid processing of the slides, online consultations for a more consensual diagnosis and allowing for an expert opinion in remote places [4]. The field of digital pathology makes a large amount of visual data available for automatic analysis, facilitating the visualization and interpretation of cell and tissue samples in high resolution images with the help of computer tools. The machine learning and the deep learning algorithms have to be optimized with the traditional feature extraction techniques which would avoid the subjective errors including missing a particular field, reducing inter- slide variability and allow pathologists to concentrate on the most difficult cases and result in an even deeper understanding of the pathologic processes [5-8].

Cancer is the most popular field of scientific research, being a leading cause of morbidity and mortality worldwide [9]. The field is advancing exponentially with newer updates, variants and classifications making it challenging for the histopathologists to keep a pace [10].

Pathology AI (Artificial Intelligence) system is a computer program that assists the pathologists by providing automated pathology [11]. The possible applications in the field of cancer diagnosis include risk assessment, early diagnosis, prognosis, and precision medicine.

The machine learning approaches have been used effectively for the accurate diagnosis and treatment of various cancer [12].

The advent of whole slide imaging (WSIs) led to the application of medical image analysis techniques, machine learning, and, more recently, deep learning techniques for aiding pathologists in inspecting WSIs and diagnosing cancer [13]. In particular, deep convolutional neural networks (CNNs) have shown state-of-the-art results in a large number of computer vision and medical image analysis applications [14].

Various computational pathology applications include tumor classification and segmentation,

mutation classification, outcome prediction and precision medicine, analyzing the tumor microenvironment, i.e., tumor-stroma ratio and segmentation of the microenvironment cells [15,16].

Practical Applications of Digital Pathology

A comprehensive literature search in PubMed, Medline, Embase, and Scopus using the terms Digital Pathology, IHC, CA breast, Prostate, ca colon was done.

The interpretation of gastric and colonic epithelial tumors would be of high benefit in easing the ever increasing workloads on pathologists, especially in remote locations having a limited access to the diagnostic services [17,18].

Chen *et al.* presented a new method aiming to detect flowing colon cancer cells at high-throughput rates, extracting several biophysical features and then building a deep fully connected network [19].

The system developed by Cossato *et al.* achieves a three-fold increase in the likelihood of catching cancers missed by pathologists and can be used to double-check the clinician's diagnoses [20].

The digital pathology reporting has been standardized for the classification of lymphomas [21], clear cell RCC [22], glioblastoma multiforme and medulloblastomas [23-28].

A CAD based on CNN has been used with a high accuracy for classifying endometrial biopsies and detection of endometrioid adenocarcinoma [29,30].

Breast cancer detection with a 90% accuracy has been reported by Noel *et al.* [31]. The Cancer Genome Atlas (TCGA) Program/*BrcaSeg* model involves the epithelial/stromal tissue maps for breast cancer slide images paired with gene expression data. The epithelial and stromal ratios are correlated to analyze the relationship between gene expression and tissue ratios [32]. The use of Autoencoder can be used to construct an end-to-end network model for breast cancer histopathological image classification [33,34].

Automatically derived image features can predict the prognosis of lung cancer patients and thereby contribute to precision oncology by the fully automated microscopic pathology image features [35]. An Improved diagnostic accuracy of trained histopathologists for the assessment of cutaneous melanoma has been reported [36,37]. Use of CNN for prostate histopathology image classification targeting the Gleason grading on prostate images reports an improved classification performance [38,39]. Newer Softwares have been developed to identify the malignant neuropathological features autonomously and map immunohistochemical data simultaneously [40]. Digital pathology is also showing a significant contribution in the fields of immunohistochemistry (IHC) which is crucial to develop targeted treatment and evaluate prognosis for cancer patients [41,42]. A quantitative assessments of lymphocyte clustering patterns, as well as characterization of the interrelationships between TILs and tumor regions (Immunoscore) would highlight the TIL patterns linked to tumor and immune molecular features, cancer type, and outcome [43].

With the ever advancing fast paced field of digital pathology, this article might be a tip of the iceberg. Every field of the organ specific histopathology along with the fields of immunohistochemical markers is making newer advancements and algorithms which can be impossible to address in a comprehensive review.

References

1. NIH – NCI <https://www.cancer.gov/publications/dictionaries/cancer-terms>.
2. Gurcan MN, Boucheron LE, Can A, Madabhushi A, Rajpoot NM, Yener B. Histopathological image analysis: a review. IEEE Rev Biomed Eng. 2009;2:147-71.
3. Jahn SW, Plass M, Moinfar F. Digital Pathology: Advantages, Limitations and Emerging Perspectives. J Clin Med. 2020 Nov 18;9(11):3697.
4. Marini N, Marchesin S, Otálora S, Wodzinski M, Caputo A, van Rijthoven M, et al. Unleashing the potential of digital pathology data by training computer-aided diagnosis models without human annotations. NPJ Digit Med. 2022 Jul 22;5(1):102.
5. Janowczyk A, Madabhushi A. Deep learning for digital pathology image analysis: A comprehensive tutorial with selected use cases. J Pathol Inform. 2016 Jul 26;7:29.
6. Zarella MD, Yeoh C, Breen DE, Garcia FU. An alternative reference space for H&E color normalization. PLoS One. 2017 Mar 29;12(3):e0174489.
7. Jimenez-del-Toro O, Otálora S, Andersson M, Eurén K, Hedlund M, Rousson M, et al. Analysis of Histopathology Images: From Traditional Machine Learning to Deep Learning. In: Biomedical Texture Analysis. Elsevier; 2017. p. 281-314.
8. Yang H, Kim JY, Kim H, Adhikari SP. Guided Soft Attention Network for Classification of Breast Cancer Histopathology Images. IEEE Trans Med Imaging. 2020 May;39(5):1306-15.
9. Omar M, Alexanderani MK, Valencia I, Loda M, Marchionni L. Applications of Digital Pathology in Cancer: A Comprehensive Review. Annual Review of Cancer Biology. 2024 Jun 12;8(1):245-68.
10. Sulaieva O, Dudin O, Koshyk O, Panko M, Kobylak N. Digital pathology implementation in cancer diagnostics: towards informed decision-making. Front Digit Health. 2024 May 30;6:1358305.
11. Lange H, Luengo C. Pathology AI (Artificial Intelligence) Reference Guide. Available from: https://digitalpathologyassociation.org/data/cms_files/files/PathologyAI_ReferenceGuide.pdf
12. Baxi V, Edwards R, Montalto M, Saha S. Digital pathology and artificial intelligence in translational medicine and clinical practice. Mod Pathol. 2022 Jan;35(1):23-32.
13. Kumar N, Gupta R, Gupta S. Whole Slide Imaging (WSI) in Pathology: Current Perspectives and Future Directions. J Digit Imaging. 2020 Aug;33(4):1034-40.
14. Khosravi P, Kazemi E, Imielinski M, Elemento O, Hajirasouliha I. Deep Convolutional Neural Networks Enable Discrimination of Heterogeneous Digital Pathology Images. EBioMedicine. 2018 Jan;27:317-28.
15. Arevalo J, Cruz-Roa A, Arias V, Romero E, González FA. An unsupervised feature learning framework for basal cell carcinoma image analysis. Artif Intell Med. 2015 Jun;64(2):131-45.
16. Musulin J, Štifić D, Zuljani A, Čabov T, Dekanić A, Car Z. An Enhanced Histopathology Analysis: An AI-Based System for Multiclass Grading of Oral Squamous Cell Carcinoma and Segmenting of Epithelial and Stromal Tissue. Cancers (Basel). 2021 Apr 8;13(8):1784.
17. Boquet I, Kassambara A, Lui A, Tanner A, Latil M, Lovera Y, et al. Comparison of Immune Response Assessment in Colon Cancer by Immunoscore (Automated Digital Pathology) and Pathologist Visual Scoring. Cancers (Basel). 2022 Feb 24;14(5):1170.

18. Iizuka O, Kanavati F, Kato K, Rambeau M, Arihiro K, Tsuneki M. Deep Learning Models for Histopathological Classification of Gastric and Colonic Epithelial Tumours. *Sci Rep*. 2020 Jan 30;10(1):1504.
19. Chen CL, Mahjoubfar A, Tai LC, Blaby IK, Huang A, Niazi KR, Jalali B. Deep Learning in Label-free Cell Classification. *Sci Rep*. 2016 Mar 15;6:21471.
20. Cosatto E, Laquerre PF, Malon C, Graf HP, Saito A, Kiyuna T, et al. Automated gastric cancer diagnosis on H&E-stained sections; Itraining a classifier on a large scale with multiple instance machine learning. *Proceedings of the SPIE*. 2013; 8676:867605.
21. Achi HE, Belousova T, Chen L, Wahed A, Wang I, Hu Z, et al. Automated Diagnosis of Lymphoma with Digital Pathology Images Using Deep Learning. *Ann Clin Lab Sci*. 2019 Mar;49(2):153-60.
22. Zhu M, Ren B, Richards R, Suriawinata M, Tomita N, Hassanpour S. Development and evaluation of a deep neural network for histologic classification of renal cell carcinoma on biopsy and surgical resection slides. *Sci Rep*. 2021 Mar 29;11(1):7080.
23. Roetzer-Pejrimovsky T, Moser AC, Atli B, Vogel CC, Mercea PA, Prihoda R, Gelpi E, Haberler C, Höftberger R, Hainfellner JA, Baumann B, Langs G, Woehrer A. The Digital Brain Tumour Atlas, an open histopathology resource. *Sci Data*. 2022 Feb 15;9(1):55.
24. Janowczyk A, Madabhushi A. Deep learning for digital pathology image analysis: A comprehensive tutorial with selected use cases. *J Pathol Inform*. 2016 Jul 26;7:29.
25. Chang H, Zhou Y, Borowsky A, Barner K, Spellman P, Parvin B. Stacked Predictive Sparse Decomposition for Classification of Histology Sections. *Int J Comput Vis*. 2015 May;113(1):3-18.
26. Cruz-Roa A, Arevalo J, Basavanahally A, Madabhushi A, González F. A comparative evaluation of supervised and unsupervised representation learning approaches for anaplastic medulloblastoma differentiation. In: 10th International Symposium on Medical Information Processing and Analysis. *Proceedings of the SPIE*. 2015 Jan 28;9287:76-81.
27. Otálora S, Cruz-Roa A, Arevalo J, Atzori M, Madabhushi A, Judkins AR, et al. Combining Unsupervised Feature Learning and Riesz Wavelets for Histopathology Image Representation: Application to Identifying Anaplastic Medulloblastoma. In: Navab N, Hornegger J, Wells WM, Frangi A, editors. *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*. Cham: Springer International Publishing; 2015. p. 581-8. (Lecture Notes in Computer Science; vol. 9349).
28. Han J, Fontenay GV, Wang Y, Mao JH, Chang H. Phenotypic characterization of breast invasive carcinoma via transferable tissue morphometric patterns learned from glioblastoma multiforme. *Proc IEEE Int Symp Biomed Imaging*. 2016 Apr;2016:1025-8.
29. Thompson EF, Huvila J, Jamieson A, Leung S, Lum A, Offman S, et al. Variability in endometrial carcinoma pathology practice: opportunities for improvement with molecular classification. *Mod Pathol*. 2022 Dec;35(12):1974-82.
30. Sun H, Zeng X, Xu T, Peng G, Ma Y. Computer-Aided Diagnosis in Histopathological Images of the Endometrium Using a Convolutional Neural Network and Attention Mechanisms. *IEEE J Biomed Health Inform*. 2020 Jun;24(6):1664-76.
31. Noël H, Roux L, Lu S, Boudier T. Detection of high-grade atypia nuclei in breast cancer imaging. In: Gurcan MN, Madabhushi A, editors. *Orlando, Florida, United States*; 2015. p. 94200R.
32. Lu Z, Zhan X, Wu Y, Cheng J, Shao W, Ni D, et al. BrcaSeg: A Deep Learning Approach for Tissue Quantification and Genomic Correlations of Histopathological Images. *Genomics Proteomics Bioinformatics*. 2021 Dec;19(6):1032-42.
33. Ibrahim A, Gamble P, Jaroensri R, Abdelsamea MM, Mermel CH, Chen PC, et al. Artificial intelligence in digital breast pathology: Techniques and applications. *Breast*. 2020 Feb;49:267-73.
34. Liu M, He Y, Wu M, Zeng C. Breast histopathological image classification method based on autoencoder and siamese framework. *Information*. 2022 Feb 24;13(3):107.
35. Yu KH, Zhang C, Berry GJ, Altman RB, Ré C, Rubin DL, et al. Predicting non-small cell lung cancer prognosis by fully automated microscopic pathology image features. *Nat Commun*. 2016 Aug 16;7:12474.
36. De Logu F, Ugolini F, Maio V, Simi S, Cossu A, Massi D, et al. Recognition of Cutaneous Melanoma on Digitized Histopathological Slides via Artificial Intelligence Algorithm. *Front Oncol*. 2020 Aug 20;10:1559.
37. Grant SR, Andrew TW, Alvarez EV, Huss WJ, Paragh G. Diagnostic and Prognostic Deep Learning Applications for Histological Assessment of Cutaneous Melanoma. *Cancers (Basel)*. 2022 Dec 17;14(24):6231.
38. Eloy C, Marques A, Pinto J, Pinheiro J, Campelos S, Curado M, et al. Artificial intelligence-assisted cancer diagnosis improves the efficiency of pathologists in prostatic biopsies. *Virchows Arch*. 2023 Mar;482(3):595-604.
39. Marini N, Otálora S, Müller H, Atzori M. Semi-supervised training of deep convolutional neural networks with heterogeneous data and few local annotations: An experiment on prostate histopathology image classification. *Med Image Anal*. 2021 Oct;73:102165.
40. Bao G, Wang X, Xu R, Loh C, Adeyinka OD, Pieris DA, et al. PathoFusion: An Open-Source AI Framework for Recognition of Pathomorphological Features and Mapping of Immunohistochemical Data. *Cancers (Basel)*. 2021 Feb 4;13(4):617.
41. Van Herck Y, Antoranz A, Andhari MD, Milli G, Bechter O, De Smet F, et al. Multiplexed Immunohistochemistry and Digital Pathology as the Foundation for Next-Generation Pathology in Melanoma: Methodological Comparison and Future Clinical Applications. *Front Oncol*. 2021 Mar 29;11:636681.
42. Chen Z, Zhang J, Che S, Huang J, Han X, Yuan Y. Diagnose like a pathologist: Weakly-supervised pathologist-tree network for slide-level immunohistochemical scoring. In: *Proceedings of the AAAI Conference on Artificial Intelligence 2021* May 18;35(1):47-54.
43. Saltz J, Gupta R, Hou L, Kurc T, Singh P, Nguyen V, et al. Spatial Organization and Molecular Correlation of Tumor-Infiltrating Lymphocytes Using Deep Learning on Pathology Images. *Cell Rep*. 2018 Apr 3;23(1):181-93.e7.