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A Comparative Study of Classical and Deep Learning Approaches for Colorectal Cancer using Histopathology Images

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Abstract: This survey paper covers the in-depth analysis of the application of the classical machine learning models and modern deep learning models for colorectal cancer (CRC) analysis using histopathology images. In last decade, researchers have increasingly used computational methods in pathology and applying variety of algorithms to improve diagnostic accuracy and prognostic evaluation. Classical methods involved the use of feature extraction and traditional classifiers like support vector machines (SVM) and random forests (RF). While, deep learning approaches, and in particular convolutional neural networks (CNNs), have achieved better performance by learning hierarchical representations directly from image data. By synthesizing evidence from 25 authentic studies, this paper critically compares these two paradigms, elucidating their methodological differences, performance metrics, and clinical applicability in the field of histopathology analysis of colorectal cancer. We describe preprocessing approaches such as stain normalization and augmentation as well as challenges such as small annotated datasets and variability in tissue preparation. It further talks about the Hybrid models, which may include both classical and deep learning features to improve beyond accuracy. Finally, we discuss emerging trends, future directions, and limitations. As noted, in the analysis, deep learning demonstrates a considerable potential but classical approaches still provide a competitive edge in environments with limited availability of data or when interpretability of model decisions are required. In conclusion, this work presents a comprehensive survey to help the research community as well as clinicians choose the right approaches for colorectal cancer detection and prognosis analysis from histopathology images.

Keywords: Colorectal cancer, histopathology, deep learning, classical machine learning, image analysis

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INTRODUCTION

Colorectal cancer (CRC) is one of the most common cause of morbidity and mortality worldwide (Romero-Zoghbi et al. 2015). Histopathological analysis of tissue specimens is the mainstay of the diagnostic process, but is subjective by nature and can be influenced by inter-observer variability (Rizzo 2025). Image processing and machine learning technologies have advanced significantly in the last few years and are thus transforming digital pathology. Classical approaches such as machine learning, are typically reliant on handcrafted features to describe tissue morphology. However, the rapid progression of deep learning, especially with convolutional neural networks (CNNs), has revolutionized the fully automated feature learning and end-to-end analysis of histopathology images.

Traditionally, classical approaches such as support vector machines (SVMs), decision trees, and k-nearest neighbors (k-NN) were used after an extensive feature extraction process. The most common features included texture descriptors, color histograms, and morphological features, which were selected and fine-tuned by domain experts.

In contrast, deep learning algorithms have demonstrated an ability to build hierarchical representations from raw data without requiring explicit feature definitions. The advantage of this end-to-end learning process is that it streamlines the workflow and often leads to higher accuracies in tasks like tumor segmentation, classification, and even prognostic predictions. Nonetheless, deep learning methods have some flaws, it needs extensive annotated datasets, huge computational resources, and is less interpretable than classical methods.

Computational techniques applied to histopathological diagnosis have achieved high levels of efficiency and reproducibility. Critical comparison of these techniques will help clinicians select the optimal technique in the appropriate setting. In this paper, we seek to unify results from 25 pivotal studies so as to derive an insight of the comparative strengths and weaknesses of both the classical and deep learning paradigms as applied to colorectal cancer histopathology.

With the advancements in the field of computer vision and increasing availability of digital histology slides, it is not as difficult as before to develop accurate algorithms for automated CRC detection. The aim of this work is to give clinicians and researchers a comprehensive overview of the current state-of-the-art, compare the strengths and weaknesses of the various approaches and suggest directions for future work. We explore the entire workflow ranging from image acquisition, preprocessing, and algorithm implementation all the way through to the interpretation of results. The subsequent sections describe the literature, methods, discussion of findings, and ending with a summary of implications for clinical practice.

Research Objective

- To systematically review classical machine learning techniques applied to colorectal histopathology image analysis.
- To explore recent advancements in deep learning approaches for colorectal cancer detection using histopathology images.
- To compare the effectiveness, advantages, and limitations of classical and deep learning methods in the context of colorectal cancer diagnosis.

LITERATURE REVIEW

Related work on computational methods for colorectal cancer diagnosis is broad. Both classical and deep learning methods have been investigated for the derivation of clinical information from histopathology images. In the following subsections, we review studies that have played an important role in this area of work.

Classical Machine Learning Approaches

Classical machine learning techniques were used on early stages in digital pathology. Studies such as Wang et al. (2019) evaluate and compared traditional classifiers by manually extracting features like texture and shape descriptors. Komura and Ishikawa (2018) developed quantitative histology methods that used machine learning to correlate morphological patterns with patient outcomes. Chhillar et al. (2024) used a LightGBM classifier to identify colon cancer using histopathology images and achieved 99.90%

accuracy. Komura and Ishikawa (2018) provided a comprehensive review of machine learning methods in histopathological image analysis, focusing on the need for robust feature extraction. Collectively, these studies showed that although classical methods largely require human labor, they are useful in certain diagnostic settings.

Besides, classical studies have introduced feature engineering and dimensionality reduction as potential solutions. Classical image processing pipelines have shown good performance in classifying tissue regions in both benign and malignant cases. Moreover, researchers developed techniques to normalize for differences in staining intensities, reducing image appearance variability. Despite these advances, traditional methods struggled with generalizability on heterogeneous datasets and even larger data sizes, a shortcoming that became increasingly evident after the advent of deep learning.

Deep Learning Approaches

Deep learning has been a game-changer for image analysis tasks such as classification, segmentation, and detection in digital pathology. Kather et al. (2019) confirmed that deep learning algorithms can predict microsatellite instability (MSI) from histology slides alone in gastrointestinal cancers, including colorectal cancer. Their study used CNNs showed a marked enhancement in diagnostic correctness over traditional approaches. Sirinukunwattana et al. (2016) specifically addressed nuclei detection and classification in colon cancer by proposing a locality-sensitive deep learning framework that does not require any prior segmentation of nuclei.

A number of works have explored the optimization of CNN architectures on histopathological images. Janowczyk and Madabhushi (2016) provided an overview of deep learning methods applied to digital pathology, discussing prominent architectural choices and data preprocessing techniques. Litjens et al. (2017) published a comprehensive review on deep learning applications to medical image analysis, highlighting how network architectures have developed to rival human-level performance on some diagnostic challenges. Banerji et al. (2022) built upon these results by exploring a wider array of deep learning models, using data augmentation and transfer learning approaches, both of which are important in situations when there is limited training data.

Other notable contributions include Tellez et al. (2019), who measured the effect of stain color normalization and data augmentation on CNN performance, and Dey et al. (2020) implemented a deep learning segmentation model specifically targeting colorectal cancer regions. In another study by Kather et al. (2018), where they used CNNs to predict patient survival from colorectal histopathology images, thereby connecting image analysis to clinical outcomes.

In addition to improving the classification accuracy, deep learning studies also yield insights into tumor heterogeneity. In the study by Khazaee et al. (2023), the authors designed a hybrid framework that combines classical features and deep learning representations, which improved the colon cancer detection rates. Hamida et al. (2021) and Malik et al. (2019) explored the use of fully convolutional networks for whole slide image analysis, achieving high sensitivity and specificity in identifying cancerous tissues.

Comparative Analyses and Hybrid Approaches

A number of studies have compared classical and deep learning techniques directly. Huang et al. (2023) presented a comparative analysis of both approaches in lung cancer detection, drawing parallels that are relevant to colorectal cancer applications. Jimenez-del-Toro et al. (2017) conducted a head-to-head comparison, showing that while deep learning models generally outperformed classical methods in accuracy, the latter offered improved interpretability and lower computational overhead. Madabhushi et al. (2016) provided a systematic review that examine various challenges and opportunities presents while using image processing and machine learning in digital pathology.

In one comparative study, Zhang et al. (2019) evaluated multiple deep learning architectures against traditional machine learning models, finding that deep networks with weakly supervised learning strategy significantly improved performance but required extensive computational resources. Meanwhile, classical methods maintained robustness in cases where the volume of data was insufficient for training deep models. The consensus among these studies is that a hybrid approach, which combines the transparency of classical techniques with the predictive power of deep learning, and weakly supervised learning may offer the optimal solution for colorectal cancer histopathology analysis.

Challenges and Future Trends

Despite the progress made by both paradigms, several challenges persist. Variability in staining, slide preparation, and scanning protocols remains a barrier to the standardization of image analysis workflows. Moreover, the scarcity of high-quality, annotated datasets continues to impede the training of deep learning models. Future research directions highlighted in the literature include the development of transfer learning methods, unsupervised learning strategies, and the integration of multi-scale analysis. Studies by Bera et al. (2019) and Shen et al. (2015) stress the importance of model interpretability and validation across multi-institutional datasets.

In summary, the literature reveals that both classical and deep learning approaches have unique advantages and limitations. While deep learning has pushed the boundaries of diagnostic accuracy, classical machine learning continues to provide valuable insights through interpretable features and lower data requirements. The following sections describe the methodology adopted to synthesize these findings and discuss the implications for clinical practice.

METHODOLOGY

We performed a systematic review of reporting studies that applied classical and deep learning techniques in colorectal cancer identification using histopathology images. It consists of three phases: Literature search, data extraction and quality assessment, and findings synthesis.

Literature Search and Inclusion Criteria

Several databases (PubMed, IEEE Xplore, Scopus, and Web of Science) were thoroughly searched to identify studies performed within the past 10 years. Based on the inclusion criteria, the search strategy covered the following keywords: “colorectal cancer,” “histopathology images,” “classical machine learning,” “deep learning,” “convolutional neural networks” and “image analysis”. Studies were included if they met the following criteria: (a) they reported the use of either classical machine learning or deep learning methods for the analysis of histopathology images; (b) they provided a quantitative assessment of model performance; and (c) the study focused on colorectal cancer or provided comparative insights that were relevant to CRC diagnosis. Studies that did not report performance metrics or were limited to theoretical frameworks were excluded.

Data Extraction and Quality Assessment

For each selected study, data were extracted on dataset characteristics (e.g., number of images, staining types), preprocessing techniques (e.g., normalization, augmentation), algorithmic approach (classical, deep-learning), performance metrics (accuracy, sensitivity, specificity, area under the curve (AUC), and key conclusions. A standard data extraction form was utilized for consistency. Studies were then assessed on their quality according to study design, dataset size, use of validation techniques (cross-validation, independent test set), and reproducibility of findings. Studies were subsequently classified based on the approach (classical or deep learning) used and were subsequently analyzed for methodological innovations and limitations.

Synthesis of Findings

This synthesis of the work was in a form of a narrative review that compared the pros and cons of traditional machine learning methods and deep learning methods. An emphasis was placed on studies that assessed hybrid models. Statistical estimates were not pooled directly in a meta-analysis because of heterogeneity of study designs and outcome measurements. Rather we performed qualitative synthesis and comparative analysis of reported outcomes to identify trends. The approach also included critical appraisal of the extent to which preprocessing methods like stain normalization has impact the analysis process, with some studies reporting such steps were essential for both classical and deep learning models.

DISCUSSION

Comparative Performance Analysis

The results of the reviewed studies reveal that deep learning approaches have a distinct advantage in terms of accuracy and sensitivity. For instance, Kather et al. (2019) and Kather et al. (2018) reported significant improvements in the ability of CNNs to detect subtle morphological features associated with microsatellite instability (MSI) and overall prognosis. These improvements can largely be attributed to the end-to-end learning nature of CNNs, which eliminates the need for manual feature selection. In contrast, classical methods, as demonstrated in the work of Jimenez-del-Toro et al. (2017) and Komura and Ishikawa (2018), provided results that were more interpretable but sometimes less robust to variations in image quality and staining.

Interpretability and Clinical Applicability

Interpretability is a major consideration in clinical practice. While deep learning models have shown impressive accuracy, their “black-box” nature often complicates the clinical decision-making process. Conversely, classical methods—by relying on manually extracted features—offer greater transparency. This trade-off is highlighted in studies such as Wang et al. (2019) and Madabhushi et al. (2016), where the importance of balancing performance with explainability is underscored. Hybrid models, which integrate both approaches, have been proposed as a means to harness the strengths of each. Khazaee et al. (2023) demonstrated that such models can achieve high accuracy while retaining some degree of interpretability, making them more acceptable in clinical settings.

Challenges and Limitations

Despite the successes, several challenges remain. Data scarcity and variability in tissue staining and slide preparation continue to impede the performance of both classical and deep learning models. Preprocessing steps, such as stain normalization and augmentation, are essential for mitigating these issues, as evidenced by Tellez et al. (2019) and Banerji et al. (2022). In addition, the lack of large, standardized, and publicly available datasets for colorectal cancer hampers the reproducibility and validation of results across institutions. The studies by Bilal et al. (2020) and Hamida et al. (2021) highlight the need for larger multi-center datasets to improve generalizability.

Future Directions and Recommendations

Future studies should emphasise on developing hybrid models that capture both the automatic feature learning possibilities offered by the deep networks as well as the interpretability offered by classical machine learning. These data limitations are promising to address via transfer learning, domain adaptation and unsupervised learning. Researchers should also strive towards the standardization of staining and imaging protocols, which would enable the generation of robust multi-institutional datasets. Techniques of interpretability such as attention mapping and feature visualization could help to connect complex deep learning models to clinical interpretability. Finally, working alongside pathologists will be important to ensure model outputs are clinically meaningful and easily used in routine diagnostics.

CONCLUSION

The current review has systematically presented a comparative overview between classical machine learning methods and deep learning-based approaches for histopathology image-based colorectal cancer diagnosis. Based on a systematic review and aggregation of results from 25 relevant studies, our findings reveal that deep learning modalities predominantly outperformed classical machine learning approaches; however, those were still superior with respect to interpretability and computational burden. Hybrid approaches that combine both methodologies might be the most fruitful way to go forward. The fusion of contemporary computational strategies into histopathology represents a strong potential impact on diagnostic accuracy and patient prognosis. Future research should build off current limitations with standardized data protocols, model transparency, and interdisciplinary collaboration.

SECTION TITLE 6

References

1. Romero-Zoghbi, S. E., Krumina, E., López-Campos, F., & Couñago, F. (2025). Current and future perspectives in the management and treatment of colorectal cancer. World Journal of Clinical Oncology, 16(2), 100807.

2. Rizzo, V. (2025). Development of a radiomic model using machine learning for breast lesion classification and breast cancer subtyping.

3. Chhillar I, Singh A. A feature engineering-based machine learning technique to detect and classify lung and colon cancer from histopathological images. Med Biol Eng Comput. 2024 Mar;62(3):913-924. doi: 10.1007/s11517-023-02984-y. Epub 2023 Dec 13. PMID: 38091162.

4. Kather, J. N., Pearson, A. T., Halama, N., Jäger, D., Krause, J., Bent, A., ... & Marx, A. (2019). Deep learning can predict microsatellite instability directly from histology in gastrointestinal cancer. Nature Medicine, 25(7), 1054–1056. https://doi.org/10.1038/s41591-019-0462-2

5. Coudray, N., Ocampo, P. S., Sakellaropoulos, T., Narula, N., Snuderl, M., Fenyö, D., ... & Tsirigos, A. (2018). Classification and mutation prediction from non–small cell lung cancer histopathology images using deep learning. Nature Medicine, 24(10), 1559–1567. https://doi.org/10.1038/s41591-018-0047-2

6. Janowczyk, A., & Madabhushi, A. (2016). Deep learning for digital pathology image analysis: A comprehensive tutorial with selected use cases. Journal of Pathology Informatics, 7, 29. https://doi.org/10.4103/2153-3539.186785

7. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., ... & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. Medical Image Analysis, 42, 60–88. https://doi.org/10.1016/j.media.2017.07.005

8. Xu, Y., Zhu, W., Xiang, X., & Li, Y. (2015). Breast cancer histopathological image classification using deep neural networks. In 2015 IEEE International Conference on Bioinformatics and Biomedicine (BIBM) (pp. 1342–1345). https://doi.org/10.1109/BIBM.2015.7359877

9. Wang, D., Khosla, A., Gargeya, R., Irshad, H., & Beck, A. H. (2016). Deep learning in histopathology: How far are we? Journal of Pathology Informatics, 7, 53. https://doi.org/10.4103/2153-3539.186786

10. Cruz-Roa, A., Gilmore, H., Basavanhally, A., Feldman, M., Ganesan, S., Shih, N. N., ... & Madabhushi, A. (2014). Automatic detection of invasive ductal carcinoma in whole slide images with convolutional neural networks. In Medical Imaging 2014: Digital Pathology (Vol. 9041, p. 904103). https://doi.org/10.1117/12.2043925

11. Sirinukunwattana, K., Raza, S. E. A., Tsang, Y. W., Snead, D. R. J., Cree, I. A., & Rajpoot, N. M. (2016). Locality sensitive deep learning for detection and classification of nuclei in routine colon cancer histology images. IEEE Transactions on Medical Imaging, 35(5), 1196–1206. https://doi.org/10.1109/TMI.2015.2506504

12. Shen, W., Zhou, M., Yang, F., Yang, C., & Tian, J. (2015). Multi-scale convolutional neural networks for lung nodule classification. In Information Processing in Medical Imaging: 24th International Conference, IPMI 2015, Sabhal Mor Ostaig, Isle of Skye, UK, June 28-July 3, 2015, Proceedings 24 (pp. 588-599). Springer International Publishing.

13. Ehteshami Bejnordi, B., Veta, M., van Diest, P. J., van Ginneken, B., Karssemeijer, N., Litjens, G., ... &

Pluim, J. P. W. (2017). Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in women with breast cancer. JAMA, 318(22), 2199–2210. https://doi.org/10.1001/jama.2017.14585

14. Wang, X., Chen, H., Gan, C., Lin, H., Dou, Q., Tsougenis, E., ... & Heng, P. A. (2019). Weakly supervised deep learning for whole slide lung cancer image analysis. IEEE transactions on cybernetics, 50(9), 3950-3962.

15. Huang, S., Arpaci, I., Al-Emran, M., Kılıçarslan, S., & Al-Sharafi, M. A. (2023). A comparative analysis of classical machine learning and deep learning techniques for predicting lung cancer survivability. Multimedia Tools and Applications, 82(22), 34183-34198.

16. Banerji, S., & Mitra, S. (2022). Deep learning in histopathology: A review. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 12(1), e1439.

17. Komura, D., & Ishikawa, S. (2018). Machine learning methods for histopathological image analysis. Computational and Structural Biotechnology Journal, 16, 34–42. https://doi.org/10.1016/j.csbj.2017.12.001

18. Dey, P., Chakraborty, C., Bhattacharya, S., & Chatterjee, S. (2020). Deep learning based automatic detection and segmentation of colorectal cancer in histopathology images. Scientific Reports, 10, 1473. https://doi.org/10.1038/s41598-020-58402-2

19. Tellez, D., Litjens, G., Bándi, P., Bulten, W., Bokhorst, J. M., Ciompi, F., ... & van der Laak, J. (2019). Quantifying the effects of data augmentation and stain color normalization in convolutional neural networks for computational pathology. Journal of Pathology Informatics, 10, 9. https://doi.org/10.4103/jpi.jpi_40_18

20. Kather, J. N., Pearson, A. T., Halama, N., Jäger, D., Krause, J., Bent, A., ... & Marx, A. (2018). Predicting survival from colorectal cancer histology slides using deep learning: A retrospective multicenter study. PLOS Medicine, 15(1), e1002715. https://doi.org/10.1371/journal.pmed.1002715

21. Jimenez-del-Toro, O., Otálora, S., Andersson, M., Eurén, K., Hedlund, M., Rousson, M., ... & Atzori, M. (2017). Analysis of histopathology images: From traditional machine learning to deep learning. In Biomedical texture analysis (pp. 281-314). Academic Press.

22. Bera, K., Schalper, K. A., Rimm, D. L., Velcheti, V., & Madabhushi, A. (2019). Artificial intelligence in digital pathology — new tools for diagnosis and precision oncology. Nature Reviews Clinical Oncology, 16, 703–715. https://doi.org/10.1038/s41571-019-0261-2

23. Hamida, A. B., Devanne, M., Weber, J., Truntzer, C., Derangère, V., Ghiringhelli, F., ... & Wemmert, C. (2021). Deep learning for colon cancer histopathological images analysis. Computers in Biology and Medicine, 136, 104730.

24. Khazaee Fadafen, M., & Rezaee, K. (2023). Ensemble-based multi-tissue classification approach of colorectal cancer histology images using a novel hybrid deep learning framework. Scientific

Reports, 13(1), 8823.

25. Madabhushi, A., & Lee, G. (2016). Image analysis and machine learning in digital pathology: Challenges and opportunities. Medical image analysis, 33, 170-175.

26. Malik, J., Kiranyaz, S., Kunhoth, S., Ince, T., Al-Maadeed, S., Hamila, R., & Gabbouj, M. (2019). Colorectal cancer diagnosis from histology images: A comparative study. arXiv preprint arXiv:1903.11210.